Gender Differences in Persistence in a Field of Study[1]

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Abstract

Weaker retention of women in quantitatively oriented fields, particularly STEM[2] is widely seen in US higher education. This persistence gap is often explained by less generous grading in these fields and the conjectured tendency of female students to generally exhibit stronger "sensitivity" to grades. We examine student persistence in a wide spectrum of academic fields using a rich Indiana University Learning Analytics dataset. We find that the phenomenon of women's relatively lower persistence in STEM in response to lower grades does not universally extend to other disciplines. Further, a stronger response, in terms of attrition, to grades received is not a gender-specific characteristic but more likely to reflect gender differences in the underlying field preferences. In other words, it is a weaker preference for a field of study that is likely to make students more responsive to grades received in it, rather than the other way around as is commonly suggested.

JEL codes: I23, I24, J24, D21.

Key words: college major choice, persistence, sensitivity to grades.

[1] This project was made possible by informational support by Indiana University Bloomington Assessment and Research in the Office of Vice-Provost for Undergraduate Education along with generous funding from IU Learning Analytics Fellowship program. The views expressed in this study along with any errors and omissions are our own. We are grateful to Peter Arcidiacono, Francesca Barigozzi, Todd Kaplan, and Miguel Urquiola for incisive and helpful comments. We also acknowledge with gratitude helpful discussions with Elena Del Rey, Juan Carlos Escanciano, Stefan Weiergraeber, and the participants of the 2019 Girona Workshop on Family and Gender Economics. The responsibility for all errors and omissions is ours.

[2] The acronym derived from the names of the constituent groups of disciplines: Sciences, Technology, Engineering, and Mathematics.

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1. Introduction

A new direction of research in the economics of higher education, which developed over the last two decades, has focused on students' choices among the fields of study, as is well justified by the evidence that the choice of college major is becoming a stronger determinant of the variation in career earnings than the choice between going to college or not (see James, 2012, Hershbein and Kearney, 2014). The facts of substantial gender differences in student choices of academic disciplines are well known. The significant underrepresentation of women in STEM and Business, and their overrepresentation in the Social Sciences (excluding Economics) and Humanities (SSH) and in Education are the most salient among them (see for instance, Gemici and Wiswall, 2014).[3] In addition to lower propensity to enroll in STEM and other quantitatively oriented majors, women's higher rates of attrition from such majors (e.g., Chen and Soldner, NCES, 2013) exacerbate the imbalances in the gender breakdowns of degrees awarded in academic disciplines. The goal of this paper is to contribute to the understanding of gender differences specifically on the attrition side, i.e., in student persistence in college disciplines.

This persistence gap is often explained in the literature by less generous grading in these fields and the conjectured tendency of female students to generally exhibit stronger "sensitivity" toward grades. An alternative line of reasoning, which especially draws on the variation across disciplines in the magnitude of college premium, invokes gender differences in preferences for fields of study, including for pecuniary and non-pecuniary attributes of careers to which they lead. In this paper, we take a holistic approach to these competing explanations and demonstrate that differential responsiveness to grades can itself follow from differences in the tastes for fields. If so, gender gaps in responsiveness to grades should vary in magnitude and even in sign across fields, a potentially testable prediction. We examine student persistence in a wide spectrum of disciplines using a rich Indiana University Learning Analytics dataset. We find that the phenomenon of women's relatively lower persistence in STEM in response to lower grades indeed does not universally extend to other disciplines such as Business and Economics (BE) and Social Sciences and Humanities (SSH). Furthermore, the analysis of cross-disciplinary choices allows us to decompose the gender gap in persistence according to the taste for a field of study

[3] The former is all the more prominent given that women increasingly overtake men in the overall college enrollments, as well documented by Goldin et al. (2006), the phenomenon which a recent literature attempts to explain by differences in gender-specific college premia (Becker et al., 2010, Ashworth and Ransom, 2019).

and the taste for grades received in it as factors in students' persistence decisions. This allows us to argue that it is a weaker preference for a field of study, such as STEM, that is likely to make a student more responsive to grades received there, rather than the other way around.

Given the differences in college premia across fields, with STEM leading in lucrativity, gender imbalances described above have obvious implications for the gap in career earnings of college-educated men and women. Among potential explanations for the gender gap in the pursuit of lucrative fields in college, some authors, e.g., Montmarquette et al. (2002), Zafar (2013), Altonji et al. (2015) and Rendall and Rendall (2014), raise the conjecture that women and men tend to attach different levels of importance to pecuniary and non-pecuniary benefits associated with future occupations, whereby women place relatively lower weight on the former than do men, and higher weight on the latter.[4] Speaking more broadly, this line of reasoning points to systematic gender differences in tastes for fields of study. We thus term these explanations for gender gaps in academic field choice and persistence as *field taste-centered*.

There is also a growing literature (e.g., Montmarquette et al., 2002 and Stinebrickner and Stinebrickner, 2014) examining the effects of students' expected and actual grade performance in courses on their decisions whether to enroll and persist in the corresponding disciplines. Arcidiacono (2004), who examines a broad cross-section of disciplines, finds that although expectation of a lucrative career is a significant factor in student choices of a major, poor performance causes one to switch to a less lucrative discipline. This implies a trade-off between expected future wages associated with a discipline and the grades earned there.[5] It is indeed well recognized (e.g., Aachen and Courant, 2009) that grades vary strongly across disciplines (lower in STEM, higher in Humanities and Social Sciences, save for Economics) and that this does have an effect on student choices of majors.[6] The observed gap in favor of men in disciplines which tend to assign lower grades and a similar gap in favor of women in fields that tend to grade more

[4] These gender differences may in turn be traced back to continued, albeit diminished, gender differences in marriage and family role expectations and norms – see, e.g., a recent survey by Blau and Kahn (2017).

[5] In a similar vein, Rask (2010) and Stinebrickner and Stinebrickner (2014) further study the effects of grade performance on persistence in STEM majors and affirm the existence of such trade-off.

[6] The overall trade-off across the fields of study between expected future wage earnings associated with a discipline and its grade standards (and accordingly, the required study effort) can be well understood in the context of labor market equilibrium. Indeed, higher expected returns of an occupation are potentially balanced out, for a marginal candidate, by the higher effort cost of qualifying for it in such equilibrium.

generously lead a substantial literature to conjecture that women are characterized by relatively stronger aversion to low grades *per se* as a behavioral attribute. For instance, Rask and Tiefenthaler (2008) find strong evidence for such gender gap in "grade sensitivity" in students' decisions whether to persist in their study of Economics, while Ost (2010) suggests a similar conclusion when it comes to Physics.[7] Chen and Soldner (2013), who use NCES survey data, argue that women and minorities exhibit aversion to an excessively "competitive climate" in STEM – an increasingly common suggestion in the literature (see Niederle and Vesterlund, 2010). Ahn et al. (2019) affirm it through their estimation of a structural model of students' decisions to enroll in classes and grading policies of the faculty, which result, in equilibrium, in comparatively higher study times and lower grades in STEM, the latter being responsible for the relative under-enrollment of women. We shall therefore term these explanations of gender differences in the choice of and persistence in college majors *grade sensitivity-centered*.

To sum up, two main lines of economics reasoning offer competing explanations for gender gaps in students' decisions to enroll and persist in college disciplines. Much of the literature advances an explanation rooted in unconditional gender differences in student responsiveness to grades with conjectured women's *generally* (i.e., exhibited across all disciplines) stronger sensitivity to weak grade performance. The second line of reasoning, which we termed *field taste-centered*, is based on evidence of systematic gender differences in preferences for fields of study, including their academic content as well as pecuniary and non-pecuniary benefits associated with future careers. This explanation does not require postulating that there are general, not field-dependent gender differences in sensitivity to grades. For example, since more lucrative college majors do tend to assign relatively lower grades, the individuals who place relatively less weight on preference for the lucrativity of future careers, will be less inclined, *ceteris paribus*, to accept the lower grades and higher effort downsides of such choices. It then follows that if women attach relatively less importance to future career income than men, then they will be relatively more

[7] Feng et al. (2018), who, like we, use Indiana University data, document stronger responsiveness of women to grades received in STEM classes (particularly in relation to grades earned in other disciplines) in terms of decisions against persisting in STEM. Kugler et al. (2017) advance a richer behavioral model of gender differences in choosing a major. Similar to Ost (2010) who focused specifically on sciences, they conjecture that when women and men assess their fit and the likelihood of success in their initial major, they update their beliefs regarding their abilities based on, in addition to grades received, also on the observed demographics of the major, such as it being male- or female-dominated. They then test the predictions of this model and conclude that it takes multiple signals of the lack of fit into the major, not limited to grade performance, to make women switch more than men.

averse *endogenously* to accept poor grades in these majors, compared to male counterparts. Likewise, if hypothetically, men tend to have stronger "taste" for engineering disciplines than women, they would be relatively more tolerant of grades received there, even if their *direct* "psychological" dislike of bad grades were identical to women's. A potentially testable implication of this conjecture is that if women are found to have stronger taste for humanities, they should show relatively stronger (endogenous) tolerance for grades received there, other things equal, than their male counterparts. This reasoning is attractive in its consistency with economic analyses of individual choices in broader contexts. For instance, a consumer with a stronger taste for a particular product, such as ice-cream of a certain flavor, will exhibit relatively weaker "sensitivity" to its price compared to otherwise similar consumer who is less drawn to this flavor in favor of another.

This paper focuses specifically on gender differences in persistence in academic disciplines. It is the first, to our knowledge, to examine the gender gap in student responses to grades, in terms of persistence in an initially chosen field, across the entire spectrum of disciplines. We are able to do so by using a comprehensive Indiana University-Bloomington Learning Analytics dataset. It gives us an opportunity to investigate whether the relatively stronger overall responsiveness to grades women exhibit in STEM is sustained in other academic disciplines such as Business and Economics (BE) and Social Sciences and Humanities (SSH). Furthermore, the analysis of cross-disciplinary choices allows us to decompose the gender gap in persistence according to the *field taste-driven* and *grade sensitivity-driven* factors. In other words, we are able to estimate the relative weights of taste for a field of study and of direct grade-sensitivity (the taste for grades) as factors in students' persistence decisions, which is the main goal of this paper.

The data also allow us to examine the discipline-switching patterns of non-persisting students in more detail, particularly to differentiate student migrations from an initial academic category, e.g., STEM, by potential destination categories, such as BE, SSH, etc., depending on their performance in the classes taken in these alternative destination categories. This comprehensive characterization of student persistence and migrations throughout the entire spectrum of academic categories available at the university is novel and offers a broader outlook on gender differences in these decisions and the effects of grade performance on them.

Our empirical analysis further reveals that direct "grade sensitivity" of a student is not a gender-specific behavioral attribute *per se*, contrary to some of the theories cited above, but that gender differences in it vary across disciplines and interact with tastes for the academic fields. For instance, we find that although women tend to exhibit stronger overall responsiveness to grades than men in their patterns of migration out of STEM, this is due to men's stronger taste for it, whereas women are in fact less directly "sensitive" to grades in STEM than are men. In contrast, we find that direct grade-sensitivity is similar for men and women in BE, and stronger among women in other professional schools (OP). Overall, our results support our thesis that responsiveness to grades in academic persistence decisions predominantly reflect students' taste-driven attachments to academic disciplines, akin to the obvious fact that consumers' responsiveness to prices depends on their preferential attachment to the corresponding products. In other words, we find that it is the underlying weaker preferential attachment to a field that tends to make students more responsive to grades received in it, not the other way around.

We also offer a theoretical framework for such reasoning. We present a utilitarian model of students' decision-making about selecting a field of study. Students differ in ability (pre-college preparation) as well as in the weights they attach to utility of discipline-specific human capital, disutility of study effort required for attaining it, and psychic benefits of higher grades in the discipline. We distinguish between academically more demanding and less demanding majors, in terms of the effort it takes to attain a certain grade, controlling for student ability. We then show that the sub-population of students who have relatively stronger taste for a more demanding major will bias their self-sorting toward it. In other words, this group will have relatively lower average ability and grades in the demanding major compared to the group of students who choose this major while placing relatively lower utility weight on human capital attainment in it. A consequence of such self-sorting across majors is that the average ability and grades of the former group will be lower within each major (the more and the less demanding ones). By the same token, students who place less weight on the utility of human capital attainment in a more demanding major will exhibit "stronger" self-sorting across majors by ability, resulting in their higher average ability in each major.[8] We further apply the model to the analysis of student decisions whether to persist in an initially chosen major based, in the spirit of Manski (1989), on

[8] Assuming (as we'll indeed find) that women do tend to place lower weight on the benefits of STEM majors which have higher grading standards, the above result predicts that women should exhibit superior grade performance in STEM and non-STEM majors alike. This prediction is consistent with the descriptive statistics in all the academic categories at IU presented in the next section.

the assumption that students make their initial choices of majors with imprecise knowledge of their ability, which is then updated according to the grades received. Specifically, according to the model, a low grade received in an early stage of studies in a major will signal an accordingly low ability level and, if the grade falls below a certain cutoff, will compel the student to switch to an alternative major rather than persist. Our model shows that the threshold grade level in question is in inverse relation with the weight a student places on the taste for human capital acquired in the initial major. This result helps provide an interpretation of the paper's empirical findings, consistent with the premise that women and men differ in their tastes for academic disciplines. Specifically, our model predicts that in a field for which men exhibit stronger taste than women, the threshold grade for deciding to switch out will tend to be higher for women than for men. This is aligned with our empirical results and thus renders their plausible explanation.

The paper is structured as follows: Section 2 describes the data, Section 3 outlines the econometric model, Section 4 states the results, Section 5 presents robustness checks for them. Section 6 presents a theoretical model of student decisions about selecting and/or persisting in a field of study and provides a compelling interpretation for the paper's empirical results. Section 7 concludes. Appendix contains supplemental information on the academic categories and student population, details on a robustness check, and the proofs of the key results of Section 6.

2. The Data

The data used in this paper comes from Indiana University's Learning Analytics dataset which contains detailed information for every undergraduate student enrolled at IU between Fall 2006 up through Spring 2017. It contains demographic information for each student and records his/her semester-by-semester academic activity such as every class taken and grade received there, as well as all majors declared during the student's time at IU.

We analyze academic decisions of domestic non-transfer students as they transition from their second to third year at IU.[9] A spotlight on a specific timeframe of students' decisions is essential, as decisions at different points in students' academic careers entail different opportunity costs

[9] We have excluded IU's foreign and transfer students from the Learning Analytics data set, because a substantial portion of them lack aptitude test scores and/or other pre-matriculation academic performance data, unlike their domestic non-transfer counterparts for whom this information is available. The excluded populations also feature systematic distinctions, in terms of the cost of education and, due at least in part to a related selection bias, in preferences for academic fields and other dimensions of substantial unobserved heterogeneity.

and are based on different amounts of information they possess regarding their academic interests, ability, and academic options. Our particular focus on the transition from the second semester of the second year to the first semester of the third year of studies is well justified by the fact that IU students typically finalize their selection of major at the start of the third year, by which time they have normally taken a sufficient number of pre-requisite courses allowing for a more informed decision based on their relevant performance. By the same token, by this point in their studies students face non-trivial opportunity cost of switching to a different academic category with a different set of academic pre-requisites.[10]

One possible choice for students who switch out of their current major is to drop out of the university. We identify a student as a *dropout* from Indiana University, if he/she stopped enrolling in classes for more than three semesters without having earned a degree from Indiana University. It is worth noting that the non-enrollment of a student may be due to taking a temporary break from classes. The above definition of dropping out implies, for instance, that if a student who was in his/her second year in the 2010-11 academic year, stopped enrolling at that point, and then re-enrolled in the fall of 2017 or later, i.e., after a six-year break from classes, we would still classify him/her as dropout. This definition of a dropout is supported by our analysis (available upon request) of the patterns of student breaks from classes. First, such actions are extremely rare in the second year (only 66 in the population of 50,545 took one semester break, and none took longer ones). Second, students who took more than one year off from school and ultimately re-enrolled accounted for less than 4% of the student body.

Our focus on students transitioning from their second to third year necessitates some further trimming of the dataset's population. Specifically, we only focus on students who never took a break from studies before the first semester of their third year. We also exclude students who graduated at the end of their second year (likely a result, in part, of receiving sufficient AP and summer class credits).[11] The definition of dropping out given above dictates that we have to exclude students from cohorts beyond the Spring 2013 because we need to observe students after their fifth semester for up to three semesters to distinguish between those dropping out and those

[10] The focus on decisions at half-way point in a typical duration of college studies is common in the literature. See, for instance, Arcidiacono (2004) whose analysis of NLS72 data focuses on students' migrations from the initial academic disciplines two years after the start of their studies.

[11] Among students who were active in their fourth semester since matriculating at IU, only 1.2% took a break before their fourth semester. 1.6% of this population graduated at the end of the fourth semester.

taking a short break. This leaves us with the population of 38,691 domestic non-transfer students whose transition from the second to third year of studies at IU we observe in the data set.

For the purposes of this study, we aggregate IU majors into the following five academic categories: STEM, BE, SSH, other professional schools (OP), and the School of Education (EDUC).[12] This is well justified by this paper's focus on gender differences in the patterns of persistence and migration across groups of disciplines. Our criterion for aggregating university majors into these broader academic categories is primarily based on similarity of academic foundations and tools, as is standard. The more mathematical and/or empirically analytical majors (STEM and BE) are separated from the majors that focus on reading, writing and verbal communication skills (SSH), and from the majors that focus on developing professional career-specific skills (OP and EDUC). This academic categorization also corresponds well with the breakdown of majors in terms of broad classification of post-graduation careers and is consistent with the existing literature, which allows for easier comparison of results.

As a result of the aggregation, we ignore student migration across majors within the same category. For example, students who switch from Chemistry to Biology are seen in the aggregated analysis as having persisted in STEM. It is worth noting that migrations across our broad academic categories (e.g., from Chemistry in STEM to English in SSH) are substantially costlier, in terms of time and effort, than those within a category (from Chemistry to Biology, both in STEM). Indeed, the former entails fulfilling a new set of general prerequisites, even before qualifying for taking courses specific to the new major. Accordingly, such migrations are also characterized by acquiring qualitatively different skill sets. Thus, our focus on migrations across broad academic categories puts an emphasis on the most fundamental changes in students' academic trajectories, which are also the most consequential for subsequent career choices.

The following Table 1 helps establish a general sense of student attrition by academic category aggregating outflows from and inflows into each category throughout students' entire careers at IU. The table reports this aggregate information for student cohorts matriculating in respective categories from the Fall 2006 through Fall 2010, whereby the exclusion (for the purposes of Table 1 only) of student cohorts beyond Fall 2010 ensures that the *entire* IU careers of remaining

[12] STEM categorization of majors follows that of the Department of Homeland Security. See Table A.1 in the Appendix for the full list of academic units included in this and other academic categories.

students (from their first to final academic action at IU) are observed in the data covered in the table. The Proportion columns report the breakdown of initial (at matriculation) and graduating male and female student populations by academic category.

Table 1. Graduate Shares by Academic Category for 2006-2010 Cohorts

Starting Category	Initial Size		Proportion		BA/BS		Proportion	
	Female	Male	Female	Male	Female	Male	Female	Male
STEM	2,063	2,151	13%	15%	1,495	1,854	12%	17%
BE	2,647	6,003	16%	41%	2,073	4,679	17%	43%
SSH	8,094	5,395	50%	37%	5,038	2,919	41%	27%
OP	2,573	947	16%	6%	3,328	1,480	27%	13%
EDUC	962	163	6%	1%	336	58	3%	1%
TOTAL	16,339	14,659	100%	100%	12,270	10,990	100%	100%

Two remarkable patterns emerge from Table 1: the SSH share in student choices shrinks substantially by the time of graduation, and the share of OP disciplines rises even more significantly. The latter proves to be an attractive *ultimate* destination category despite an apparent relatively low initial appeal. For example, while 16% of female students start in OP, this category's share in the graduating female population is 27%.

Table 2 details the type of action taken by students in transition between the second and third years of their studies. It shows the numbers of students who were in a given academic category during their second year and then persisted in it or took a different action by the start of their third year, with the percentages of each chosen action among those respective groups of students shown in the next column. Going across a row, one can see how many students remained in their original category as they transitioned into their third year, as well as how many students migrated to other categories or dropped out by the start of the third year. The bottom row shows the corresponding totals. The table offers preliminary evidence of differences in the distribution of students' category decisions in their third year across the starting academic categories.

Table 2. Academic category choice in 3rd year for given starting category

Second Year Category		Third Year Category											
Category	Size	STEM		BE		SSH		OP		EDUC		Drop	
STEM	6,692	6,093	91%	50	1%	152	2%	150	2%	0	0%	247	4%
BE	11,499	114	1%	10,783	94%	133	1%	186	2%	4	0%	279	2%
SSH	12,767	157	1%	149	1%	11,448	90%	338	3%	51	0%	624	5%
OP	7,805	44	2%	52	1%	115	1%	7222	93%	17	0%	355	5%
EDUC	1,704	14	1%	0	0%	19	1%	28	2%	1,593	93%	61	4%
TOTAL	40,467	6,422	16%	11,034	27%	11,867	29%	7924	20%	1,665	4%	1,566	4%

To better understand whether there are gender differences in academic decisions at the beginning of the third year at IU, we further provide in Table 3 the transition probabilities for men and women across academic categories conditional on a student's starting (i.e., year two) category. From this table, we observe that there is substantial difference between men's and women's persistence for each starting category. For example, among STEM-starters, 90 percent of women persist, and 92 percent of men do so. In contrast, among SSH-starters, female persistence rate of 92 percent is much higher than men's, which is 87 percent.[13] Note that switching to Education from other categories is very rare, less than 0.5 percent.

Table 3. Distribution of 3rd year academic category by gender for given starting category

Second Year Category			**Third Year Category**											
Category	**Starting size**		**STEM**		**BE**		**SSH**		**OP**		**EDUC**		**Drop**	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
STEM	2,873	3,819	90%	92%	0%	1%	3%	2%	4%	1%	0%	0%	3%	4%
BE	3,435	8,064	1%	1%	95%	93%	1%	1%	2%	2%	0%	0%	1%	3%
SSH	7,798	4,969	1%	2%	1%	2%	92%	87%	3%	3%	0%	0%	4%	6%
OP	5,345	2,460	0%	1%	0%	1%	1%	2%	93%	91%	0%	0%	4%	5%
EDUC	1,468	236	0%	0%	0%	0%	1%	3%	2%	1%	94%	90%	3%	6%
Total	20,919	19,548	13%	19%	16%	39%	35%	23%	26%	13%	7%	1%	3%	4%

Since we plan to evaluate the role of taste for academic category as an explanation of gender differences in field persistence, rather than the effect of direct sensitivity of men and women to grades, we first take a general look at the aggregate grade distributions in each category for men and women compiled in the following Table 4. The grade levels provided in the left-most column represent category-specific student GPAs they accumulated by the end of their second year at IU. Specifically, for a student who is in STEM in his/her second year, we select all of the STEM courses this student has taken over their first two years and compute the average STEM-specific GPA. The procedure is analogous for other starting (i.e., second-year) categories. Our focus on category-specific GPA follows from our objective to examine how student decisions whether to persist in their starting category depend on their grade performance in its classes. Indeed, for a STEM-starter a high overall cumulative GPA may not be a good basis for predicting his/her persistence in STEM, if it owes primarily to the student's good performance in

[13] Persistence and transition patterns presented in the table are not controlled for student characteristics but intended as a preliminary glance at cross-category summary statistics of gender differences. It is also worth keeping in mind that these persistence measures apply to broad academic categories and ignore student transitions within a category.

SSH classes; rather, it might be a predictor of switching to SSH.

The descriptive statistics presented in Table 4 offer a general picture of gender differences in grade distributions across the academic categories. Student information is displayed across five grade bins, which descend from the highest-grade group toward the lowest bin which groups together students possessing the average grade below C, i.e., those struggling to meet the minimum requirements in their field.[14]

Table 4. Second Year Grade Distributions Across Academic Categories by Gender

Starting Category	STEM		BE		SSH		OP		EDUC	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
Average GPA	2.99	2.88	3.27	3.12	3.31	3.12	3.48	3.31	3.65	3.47
A+ to A-	28%	24%	38%	30%	43%	33%	59%	42%	77%	61%
B+ to B	27%	25%	38%	36%	33%	29%	29%	36%	18%	24%
B to B-	22%	23%	16%	20%	16%	21%	9%	16%	3%	10%
C+ to C	13%	15%	5%	9%	6%	11%	2%	5%	2%	1%
C- & below	10%	13%	3%	5%	2%	5%	1%	2%	0%	4%
Total	100%	100%	100%	100%	100%	100%	100%	100%	100%	100%

Three important takeaways from these statistics are: (a) women exhibit remarkably superior grade performance in all academic categories, (b) while women dominate in terms of proportion in the top-grade bin, men dominate in lower grade intervals and, moreover, this imbalance strengthens as one moves down the grade scale in all the categories, and (c) the grade levels are remarkably lower in STEM, for both women and men, compared to other academic categories.

It is notable that the superior average grade performance of women over men in all academic categories shown in Table 4 contrasts with the fact that gender differential in persistence, even without controlling for other student characteristics, varies substantially across categories. For instance, the gender differential in favor of women is especially high in SSH, even compared to categories with similar average grade levels. These descriptive statistics offer preliminary support to our conjecture that differential sensitivity to grades between men and women may not tell the whole story, and the potential roles of gender differences in tastes for the attributes of academic categories other than the prevailing grade levels are at play. In the rest of the paper, we undertake a thorough examination of gender differences in preferences for academic categories

[14] Standard conversion of letter grades into numerical GPA scale is as follows: A = 4.0; A- = 3.7; B+ = 3.3; B = 3.0; B- = 2.7; C+ = 2.3; C = 2.0; C- = 1.7, etc. The corresponding grade bins are constructed as follows: "A+ to A-" is given by (3.5, 4.0], "B+ to B" by (3.0, 3.5], "B to B-" by (2.5, 3.0], "C+ to C" by (2.0, 2.5], i.e., each 0.5 GPA units wide, while students possessing GPA of 2.0 or lower grouped together in the lowest bin.

and for grades in student academic decision.

3. Econometric Model

As we discussed in some detail in the Introduction, the differences between men's and women's decisions to persist in an academic discipline may depend (a) on the grades they receive there and thereby on hypothetical gender differences in taste for (sensitivity to) grades, and (b) on their tastes for the disciplines, which may also differ systematically between genders. In light of the argument we are advancing that a weaker taste for a discipline makes one more responsive to grades received there, it is necessary to explicitly distinguish the above two aspects of gender differences in decisions about persisting in an academic category.

To this end, we model an individual student's decision problem at the beginning of the third year of studies as follows. Each student is characterized by a 'starting', i.e., second year, academic category, and decides on his/her third-year academic category, both within the following set of options: {STEM=1, BE=2, SSH=3, OP=4, DROP=0},[15] where the last option is only a potential choice for the third year. Specifically, given her starting category k, where k=1,…,4, during the second year, student i needs to determine her category j in the coming year. This corresponds to a decision whether to persist in her starting field k, i.e., to choose j=k, to migrate to one of the other four academic categories, i.e., to choose $j \neq k$ and $j \neq 0$, or to drop out, i.e., to choose j=0.

Gender plays a key role in students' academic choices. For instance, as noted earlier, it is widely observed that women are underrepresented in STEM and BE – the "lucrative" fields, i.e., those associated with relatively high post-graduation earnings. To control for gender heterogeneity regarding taste for each category, we construct a dummy variable $Male_i$ that equals 1 if student i is male and 0 otherwise. Note that this gender heterogeneity in taste for categories captures a variety of aspects of preferences, including possible gender difference in the importance attached to future earnings associated with a category as well as its other attributes such as the intrinsic intellectual appeal and non-pecuniary aspects of careers associated with it. We thus do not attempt to distinguish between these channels of gender differences in taste for academic categories based on the choices male and female students make. It is worth noticing that the taste difference captured here is not about the general population; instead, it is the difference between

[15] We exclude Education as a potential option because switching to it from other categories is exceptionally rare. We also exclude students whose initial category is Education.

men and women who have already selected them into an initial category.

Another key variable of interest is student's *year-two cumulative category GPA*, which only accounts for the courses student *i* has taken in their 'starting' (i.e., year-two) academic category, denoted as $GPA_{ik|k}$. This variable allows us to investigate how students respond to their academic performance in their starting category when they consider whether to persist in or to migrate from it. Note that this decision also depends on a student's performance in alternative categories as students might shop around for other academic fields and decide based, in part, on their performance there. Thus, we also include students' *other category GPA* variables in the model, denoted as $GPA_{ij|k}$, where $j \neq k$. To control for the fact that grade distributions and GPA-based criteria of satisfactory performance differ across categories and thus students may view their grades obtained in different categories differently, we construct mean-adjusted GPA variables, $demeanGPA_{ij|k}$, where *j*=1,…,4. It is determined, for student i and category *j* by subtracting the average GPA in the category (across students taking classes there) from the student's cumulative GPA in it. Since not all students have taken courses outside of their starting academic categories, some would have no information regarding their performance in other fields. To control for this lack of information situation, we include four *"information absent" dummy* variables associated with the *other category GPAs,* denoted as $InfoAbsent_{ij}$; it equals zero if the student has taken courses in that field, and one otherwise.

To control for the fact that students' demographic and socio-economic characteristics besides gender as well as pre-college academic characteristics can also affect their choices of academic categories in college, we also construct a vector of student general characteristics, denoted by *X(i)*, which include demographic, socio-economic, and pre-college academic variables.

We then model individual student's indirect utility of choosing category j, denoted by $U_{ij|k}$, is expressed as follows:

$$U_{ij|k} = \alpha_{j0|k} + \alpha_{j1|k} Male_i + \gamma_{1|k} demeanGPA_{ij} + \gamma_{2|k} Male_i \times demeanGPA_{ij} + \gamma_{3|k} InfoAbsent_{ij} + \mathrm{X(i)}\delta_{j|k} + \varepsilon_{ij|k}, j = 1, \dots k \qquad (1)$$

where $\alpha_{j0|k}$ captures women's intrinsic taste toward category j, and $\alpha_{j1|k}$ captures the gap between men's and women's tastes toward each category j, whereby we allow such gap to vary across categories; $\gamma_{1|k}$ captures individual students' taste for better GPA grades not specific to an academic category, $\gamma_{2|k}$ captures the gap between men's and women's tastes toward category-specific mean-adjusted GPA, whereas $\gamma_{3|k}$ captures how students view categories where they have not taken classes, hence lack information about their performance there. Coefficient $\delta_{j|k}$ captures how student i's background other than gender influences his/her view of category j, whereby we allow such influences to be category-specific. The term $\varepsilon_{ij|k}$ represents idiosyncratic taste shocks.

The above indirect utility specification nests the two explanations described in the introduction—the *field taste-based* and *grade sensitivity-centered*. Specifically, $\alpha_{j1|k}$ captures the difference between men's and women's tastes toward the attributes of category j unrelated to grades received there (such as their pecuniary and non-pecuniary characteristics), thus representing *field taste-based* explanation for students responsiveness to grades. On the other hand, coefficient $\gamma_{2|k}$ reflects the gender difference in the taste students have directly for grades, representing the *grade sensitivity-centered* explanation of their responses to grades received in a category. Using our rich data, we first test both factors of student responsiveness to grades in order to decompose the phenomenon of substantial gender gap in it as documented in the literature.

Given a student's academic starting point and her characteristics, student *i* chooses her next year's academic category to maximize her indirect utility, as expressed below:

$$U_{ij^*|k} = max_{j=0,1,\ldots,4} U_{ij|k}$$

Due to identification issues, we normalize the deterministic part of the indirect utility that a student derives from dropping out, to zero, i.e., $\beta_{0|k} = 0$. We further assume that the taste shocks are from a type I extreme value distribution and are independent and identically distributed across categories. Consequently, we can characterize a student's academic decision using the multinomial logistic expression. That is, conditional on the student's starting point *k*, the probability of student *i* choosing action j in their third year, denoted as $\pi_{ij|k}$, is given by

$$\pi_{ij|k} = \frac{e^{X(i)\beta_{j|k}}}{1 + \sum_{n=1}^{4} e^{X(i)\beta_{n|k}}}$$

Note that only the signs of the coefficients (and not their absolute values) carry meaning by indicating the direction of a variable's marginal effect. Thus, we focus on the marginal effect, which, for a binary explanatory variable such as gender, represents the corresponding difference in the probability values.

To understand the potential effect of parameters in students' academic category preference specifications on their patterns of persistence there, we further explicitly derive the connection between the persistence rate with student category preference and taste for grades. To focus on this particular relationship, we shall henceforth ignore the role of other individual characteristics and the *information absent* dummy variables. We also suppress the individual index i for ease of exposition. Specifically, we model the probability of choosing category *j* conditional on student's gender, the full vector of all four category-specific GPAs, i.e., $GPA = \{GPA_j, j = 1, \dots, 4\}$ and the starting category *k*:

$$\Pr(choice = j | gender, GPA, k) = \frac{\exp(\alpha_{j0|k} + \alpha_{j1|k} Male + \gamma_{1|k} demeanGPA_j + \gamma_{2|k} Male \times demeanGPA_j)}{1 + \sum_{j'} \exp(\alpha_{j0|k} + \alpha_{j1|k} Male + \gamma_{1|k} demeanGPA_{j'} + \gamma_{2|k} Male \times demeanGPA_{j'})}$$

This logit form indicates that the decision to choose category *j* not only depends on individual's taste toward it and the taste for grades, but also on his/her taste toward the alternative categories. The idea is that when an individual decides on a choice between all six options, the individual weighs and compares her utility levels associated with all choices and selects the one with the highest utility; this means that only the relative utility matters instead of the absolute values.

To better understand this decision process, we further represent the probability of persistence relative to dropping out, i.e., the log odds ratios between persistence and dropout, as follows:

$$g(gender, GPA, k) \equiv log \frac{\Pr(persistence | gender, GPA, k)}{\Pr(dropout | gender, GPA, k)}$$
$$= \alpha_{j0|k} + \alpha_{j1|k} Male + \gamma_{1|k} demeanGPA_j + \gamma_{2|k} Male \times demeanGPA_j$$

This log odds ratio measures the relative likelihood of decision to persist while using dropout as a reference point. To analyze the gender differences in the relative persistence rate, we present these log odds ratios for men and women, respectively, for different GPA levels as follows:

$$g(male, GPA, k) = \alpha_{j0|k} + \alpha_{j1|k} + \gamma_{1|k} demeanGPA_j + \gamma_{2|k} demeanGPA_j$$
$$g(female, GPA, k) = \alpha_{j0|k} + \gamma_{1|k} demeanGPA_j$$

The difference between male and female log odds ratios for the same GPA levels represents the gender gap in persistence due to the gender difference in terms of the tastes for grades. That is,

$$g(male, GPA, k) - g(female, GPA, k) = \alpha_{j1|k} + \gamma_{2|k} demeanGPA_j,$$

The marginal effect of GPA on this gender difference in persistence can then be represented as

$$\frac{d(g(male, GPA, k) - g(female, GPA, k))}{d\ GPA} = \gamma_{2|k}$$

This simple analysis illustrates that gender differences in category persistence can result from a combination of factors, such as gender differences in the taste for ("sensitivity" to) grades as well as in the tastes toward the academic categories, or in the interaction between the two. In order to isolate a possible gender difference specifically in terms of the sensitivity toward grades, one needs to estimate the derivative of the difference in men's and women's log odds ratios toward grades. Such analysis, however, cannot rule out that the gender difference in category persistence can also be affected by the interaction of gender differences in tastes for grades and for the categories themselves. To empirically test both theories, we estimate the regressions and provide the results in the next section by controlling a rich set of individual-level characteristics.

4. Results: Gender Differences in Student Responses to Grades

Student population in the data set is partitioned according to students' "starting", i.e., for the purposes of our econometric experiment, second-year academic categories (STEM, BE, SSH, and OP). Note that, as noted earlier, we exclude Education as a potential option because switching to it from other categories is exceptionally rare. For a similar reason, we also exclude students whose initial category is Education. We estimate the multinomial logistic regression model and evaluate the gender effect for each of the four subpopulations separately. It is worth noting that treating students in each academic category separately allows us to consider the effect of pre-selection into their starting categories so that the estimates of subpopulation's preferences toward each category vary.

We now describe student characteristics which form the vector *X(i)* of model (1). The demographic variables include race and ethnicity. The socioeconomic variables allow us to control for financial and educational differences in students' family backgrounds. In particular, *Pell grant eligibility* is a binary variable; it equals one, if the student is eligible for Pell grant, and zero otherwise. Pell grants are awarded based on student family's low-income status, indicating financial hardship. *Residency* indicates whether the student qualifies for in-state tuition as a resident of Indiana. Since in-state resident students are charged dramatically lower tuition than non-residents[16], this variable allows us to control for significant differences in students' costs. *First-Generation Student*, a binary variable, equals one, if students' parents had no education beyond secondary. This variable provides a relevant control in view of its known effect on students' performance and choices, working through a number of channels, such as accumulation of pre-college human capital and obtaining relevant information and resources. Besides the category-specific GPA, we also include student's *GPA* at the point of matriculation at IU and *Math* and *Verbal SAT* scores[17], i.e., the pre-college academic aptitude measures, to proxy students' academic ability and the level of college preparedness. Additionally, we control for cohort fixed effects where cohort is defined by the time of student's matriculation at IU.

In what follows, we present the estimation results for the STEM, BE, SSH, and OP-starters, one-by-one. For each subpopulation, we run the regression for six different specifications of model (1). In particular, specification (a) is the simplest with neither gender difference in tastes toward categories nor toward grades. That is, we only include the demean-gpa and the dummy variable indicating the student has not taken any courses in that category, i.e., we only estimate $\gamma_{1|k}$ and $\gamma_{3|k}$, the remaining coefficients are restricted to be zero; specification (b) only allows for gender difference in their disutility towards grade; specification (c) only allows for gender difference in their tastes toward categories; specification (d) allows for both gender difference in the taste towards categories and grades; specification (e) further controls for a wide range of individual characteristics capturing student's pre-college performance - entry GPA, SAT Math and Verbal scores; and specification (f) adds the covariate of demographics - race and Pell grant eligibility.

Note that these estimation results rely on the assumption that the utility of dropping out is normalized to be zero for both women and men. This is due to the fact that an individual decision is driven by the relative utility, i.e., the comparison of utility levels across options, rather than the absolute utility levels associated with a given category. This means that we cannot identify the absolute utility level but only how it relates to the utility level of the reference option, dropping out. As a result, one must be cautious in interpreting these coefficients. This normalization does not affect, however, the prediction of each individual's persistence probability.

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[16] For the 2018-2019 academic year, nominal (i.e., pre-financial aid) tuition and fees for Indiana residents amounted to $10,681 for IU Bloomington campus, while for non-resident students the corresponding figure was $35,465.

[17] The SAT scores assigned to each student in the data set are either the ones the student submitted with his/her application to IU, or the scores obtained by a standard conversion procedure from the student's ACT scores, the alternative aptitude test, which meets IU application requirements.

After obtaining the regression estimates, we next obtain the estimated migration probabilities for each academic category/GPA/gender combination using specification (f) and present the result accordingly. We specifically examine both female and male distributions of third-year academic category decisions for each starting category and the GPA grid in it (given by GPA grid 2, 2.5, 3, 3.5, and 4). These results estimate the likelihood of a student, from a population subset defined by the corresponding combination, persisting in his/her second-year academic category or switching from it to an academic alternative, including the option of dropping out.

4.1. Analysis of STEM starters

Here, we focus on STEM-starters and first present the estimates for the regressions in Table 5. These estimates convey a few surprising features. First, the estimates for the coefficient capturing the gender difference in tastes toward grades are positive and significant for specifications d-f. This suggests that in the sub-population of STEM-starters, men dislike bad grades more than do women.[18] This finding certainly appears to contrast the common belief in the literature that women have systematically stronger distaste for bad grades than men. Second,

Table 5. Estimation Results for STEM Starters

	a	**b**	**c**	**d**	**e**	**f**
gpa_demean	1.195***	1.160***	1.192***	1.051***	0.887***	0.889***
	(0.0627)	(0.0879)	(0.0632)	(0.0871)	(0.101)	(0.102)
infor	1.292**	1.278**	1.336***	1.299**	0.871	0.883*
	(0.396)	(0.397)	(0.398)	(0.406)	(0.445)	(0.448)
male_gpa		0.0575		0.258*	0.258*	0.270*
		(0.101)		(0.111)	(0.112)	(0.113)
STEM.male			-0.0958	0.0184	0.121	0.117
			(0.138)	(0.147)	(0.155)	(0.156)
BE.male			0.268	0.425	0.616	0.597
			(0.354)	(0.366)	(0.380)	(0.384)
SSH.male			-0.474*	-0.415	-0.498*	-0.474*
			(0.212)	(0.213)	(0.223)	(0.224)
OP.male			-1.259***	-1.245***	-1.131***	-1.158***
			(0.223)	(0.224)	(0.234)	(0.235)
Pre-college performance	N	N	N	N	Y	Y
Demographics	N	N	N	N	N	Y
N	33460	33460	33460	33460	33460	33460

Standard errors in parentheses; "* p<0.05, ** p<0.01, *** p<0.001"

[18] We make this conclusion under the condition that there is no grade-gender interaction difference in students' valuation of the dropout option because the model's estimates capture only the *relative*, not absolute, utility levels.

we find that among the STEM-starters, men show stronger taste for STEM and BE than do women. On the other hand, in the subpopulation of STEM-starters, women show stronger taste toward SSH and OP than do men. Note that this gender difference is relative to the utility they attach to the dropout option. For instance, we are only able to assert that men like STEM more than women in relative terms, as compared to their respective preferences towards dropping out.

Using the estimates in column (f) we calculate the persistence and migration patterns of men and women in different grade grids and present the results in Table 6. The destination academic categories (including the option of dropping out) are represented in each panel of Table 6 by column triplets. The first two columns in each triplet report the estimates for female and male probabilities of migration from a starting category to an alternative one or the respective probabilities of persistence, in case the destination category is the same as the starting one. The third column displays the gender differential: the probability for men minus that for women, for a given pathway. Thus, positive (negative) values in the "diff" column indicate that men have a higher (lower) likelihood of persisting in or migrating to that particular category than women. For example, one can infer that for students who are in STEM in their second year and earned a cumulative GPA of 2, the estimated probability (in percentage point terms) of persisting in STEM is larger by 3.5 if the student is male rather than female. Similarly, male students starting in STEM with STEM-specific GPA grid 2 are less likely, with probability differential of -1.4%, to migrate to SSH than their female counterparts.

Table 6. STEM: Female & Male cross-category Migration and Persistence Probabilities

	STEM			BE			SSH			OP			Drop		
STEM-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	81.7%	85.2%	3.5%	1.2%	2.4%	1.2%	5.3%	3.9%	-1.4%	6.5%	2.5%	-4.1%	5.3%	6.1%	0.8%
2.5	87.4%	91.1%	3.6%	0.8%	1.5%	0.7%	3.6%	2.3%	-1.3%	4.5%	1.5%	-3.0%	3.6%	3.7%	0.0%
3	91.5%	94.8%	3.2%	0.6%	0.9%	0.3%	2.4%	1.4%	-1.1%	3.1%	0.9%	-2.2%	2.4%	2.1%	-0.3%
3.5	94.4%	97.0%	2.6%	0.4%	0.5%	0.1%	1.6%	0.8%	-0.8%	2.0%	0.5%	-1.5%	1.6%	1.2%	-0.4%
4	96.3%	98.3%	2.0%	0.2%	0.3%	0.1%	1.1%	0.4%	-0.6%	1.3%	0.3%	-1.0%	1.1%	0.7%	-0.4%

We now focus on the gender difference in persistence pattern for STEM-starters. First, *all* the reported gender differentials in the STEM persistence column are positive. This indicates that the *persistence of men in STEM exceeds that of women across all STEM grades* even after controlling for other regressors. Second, the observed gender differential widens as the grade received in STEM declines. This result can help explain the increasing under-representation of women in STEM as one moves down the grade scale. Overall, the growing gender differential implies that women are relatively more responsive to the grades they receive in STEM overall, further indicating that earned grades play a relatively larger role in female students' decisions to abandon this academic category.[19] It is important to underscore that this result is category-specific, i.e., it does not suggest that women are more responsive to grades generally, but rather that this gender difference in responsiveness to grades is specific to STEM. Most importantly, this overall women's stronger response to grades in STEM is a grand total produced by two factors: as the model shows, STEM-starting men have in fact a somewhat stronger direct taste for grades than do women, but also have a stronger taste for STEM as a field.

We now move to examine the trends in student migration to other categories. Looking back at the migration probabilities in Table 6, a not-so-surprising, general trend emerges: as student grade level decreases, the probability of migration to alternative academic categories increases, along with the probability of dropping out. We further observe that for students deciding to exit STEM, the popularity of a destination varies substantially and changes as the grade declines; these changes, moreover, can differ between genders. Specifically, *men are consistently more likely to migrate to BE than women*, as indicated by the all-positive estimates seen in BE columns. In contrast, wo*men are consistently more likely to migrate to SSH or OP than men*, as indicated by the all-negative estimates seen in these destination columns. For this latter migration trend, it is also worth noting that the gender gap in migration widens as the grade declines.

4.2 Analysis of BE-starters

Here, we focus on BE-starters and present the estimates for the regressions in Table 7. We find that for BE-starters, surprisingly, women have a stronger preference for BE than men (relative to the dropout option for each). This result appears to contradict findings in the existing literature that men tend to value BE more than women due to its lucratively. Note, however, that these findings applied to gender comparisons in the overall student population, whereas our estimate is conducted specifically on the subpopulation of BE-starters. A rationale for this result is that we compare those women and men who already revealed their predisposition toward BE by choosing it as their initial discipline. Our finding thus indicates that women who self-selected to

[19] It is noteworthy that this self-sorting phenomenon also likely contributes to the ultimate superior grade performance of women over men among students who persist in STEM.

start in BE have stronger taste for the category than men who did so. The results further show that, like in the case of STEM-starters, BE-starting women like SSH and OP more than BE-starting men, but like STEM less than do men. We also find that, in this subpopulation, men have stronger distaste for bad grades than women do.

Table 7 Estimation Results for BE Starters

	a	b	c	d	e	f
gpa_demean	1.036***	0.838***	1.015***	0.852***	0.428***	0.425***
	(0.0596)	(0.112)	(0.0599)	(0.119)	(0.123)	(0.123)
infor	0.751	0.600	0.671	0.519	-0.801	-0.795
	(0.624)	(0.637)	(0.624)	(0.642)	(0.655)	(0.657)
male_gpa		0.263*		0.210	0.241	0.240
		(0.125)		(0.131)	(0.132)	(0.132)
STEM.male			0.263	0.240	0.290	0.308
			(0.301)	(0.302)	(0.308)	(0.309)
BE.male			-0.505**	-0.481**	-0.341*	-0.366*
			(0.159)	(0.160)	(0.164)	(0.165)
SSH.male			-0.752**	-0.747**	-0.763**	-0.796**
			(0.239)	(0.239)	(0.247)	(0.249)
OP.male			-0.641**	-0.644**	-0.626**	-0.677**
			(0.223)	(0.223)	(0.231)	(0.232)
Pre-college performance	N	N	N	N	Y	Y
Demographics	N	N	N	N	N	Y
N	57475	57475	57475	57475	57475	57475

Standard errors in parentheses; "* p<0.05, ** p<0.01, *** p<0.001"

Using the estimates in column (f) we calculate the persistence and migration patterns of men and women in different grade grids and present the results in Table 8 to analyze how the bundle of gender differences in tastes toward grades and academic category jointly affect the persistence patterns. We find that among BE-starters, the persistence pattern is reverse compared to that we saw among STEM-starters. Specifically, BE-starting women display higher levels of persistence relative to their male counterparts at lower grade levels. Second, the observed gender differential

Table 8. BE: Female & Male cross-category Migration and Persistence Probabilities

	STEM			BE			SSH			OP			Drop		
BE-GPA	**Female**	**Male**	**Diff**	**Female**	**Male**	**Diff**	**Female**	**Male**	**Diff**	**Female**	**Male**	**Diff**	**Female**	**Male**	**Diff**
2	0.8%	2.0%	1.2%	91.8%	89.5%	-2.3%	2.2%	1.7%	-0.5%	2.7%	2.4%	-0.3%	2.5%	4.3%	1.9%
2.5	0.7%	1.5%	0.8%	93.2%	92.2%	-1.1%	1.8%	1.3%	-0.5%	2.3%	1.8%	-0.4%	2.0%	3.2%	1.2%
3	0.6%	1.1%	0.5%	94.4%	94.2%	-0.2%	1.5%	0.9%	-0.5%	1.9%	1.3%	-0.5%	1.7%	2.4%	0.7%
3.5	0.5%	0.8%	0.4%	95.4%	95.8%	0.3%	1.2%	0.7%	-0.5%	1.5%	1.0%	-0.5%	1.4%	1.7%	0.4%
4	0.4%	0.6%	0.2%	96.3%	96.9%	0.6%	1.0%	0.5%	-0.5%	1.3%	0.7%	-0.5%	1.1%	1.3%	0.2%

widens as the grade received in BE declines. Overall, the growing gender differential implies that men are relatively more responsive to the grades they receive in BE. It is worth noting again that this is a category-specific phenomenon.

This surprising pattern is a combined result of the workings of two factors, according to the estimated regression coefficients. First, the estimates show that men place a higher weight on the taste for grade they receive in BE (i.e., exhibit stronger “grade-sensitivity” according to the terminology we discussed in the Introduction) so that they are more responsive when the grade declines. Second, men “like” BE less, i.e., have lower corresponding taste coefficient for the field, than do women. The first of the two factors is a novel finding of our analysis, which we are able to single out thanks to considering it in combination with the second one.

A comparison to our results for STEM-starting population offers important insights. First, note that BE-starting men place a bigger weight on the taste for grades than do women, which is similar to the situation in the STEM-starting population. However, among BE-starters, men have weaker taste for their discipline than women do, whereas the situation was the opposite among STEM-starters where men “like” the discipline more than their female counterparts do. It is this specific difference in gender tastes for the categories (and not directly for good grades!), which results in the opposite persistence pattern in BE compared to STEM.

Our examination of the trends of migration from BE to other categories shows, similar to the case of STEM-starters, that as student grade level in BE decreases, the probability of migration to alternative academic categories increases, along with the probability of choosing to drop out. Furthermore, *men are consistently more likely to migrate to STEM or to drop out than women*, while women *are consistently more likely to migrate to SSH or OP than men*.

4.3 Analysis of SSH-starters

We estimate student preferences expressed in model (1) for SSH-starters and present the coefficient estimates in Table 9. They convey analogous but slightly different findings compared to the case of STEM-starting subpopulation. First of all, the gender difference in taste toward grades is positive and significant, suggesting that, again, men exhibit stronger taste toward grades than do women. This finding is similar to our analysis of STEM-starters. Second, men in this subpopulation show stronger preference for STEM and BE than do women, while women here show stronger preference for SSH and OP, relative to dropping out, compared to men.

Table 9. Estimation Results for SSH Starters

	a	b	c	d	e	f
gpa_demean	1.072***	0.960***	1.043***	0.963***	0.749***	0.738***
	(0.0469)	(0.0614)	(0.0475)	(0.0648)	(0.0736)	(0.0739)
infor	0.0838	-0.0214	0.0479	0.0697	-0.519	-0.489
	(0.273)	(0.279)	(0.273)	(0.274)	(0.290)	(0.291)
male_gpa		0.217**		0.149	0.174*	0.185*
		(0.0762)		(0.0820)	(0.0827)	(0.0827)
STEM.male			0.700***	0.719***	0.660***	0.631**
			(0.184)	(0.184)	(0.193)	(0.194)
BE.male			0.878***	0.957***	0.963***	0.966***
			(0.202)	(0.207)	(0.217)	(0.218)
SSH.male			-0.257**	-0.203*	-0.107	-0.120
			(0.0843)	(0.0898)	(0.0945)	(0.0946)
OP.male			-0.205	-0.195	-0.152	-0.182
			(0.138)	(0.139)	(0.146)	(0.146)
Pre-college performance	N	N	N	N	Y	Y
Demographics	N	N	N	N	N	Y
N	63575	63575	63575	63575	63575	63575

Standard errors in parentheses; "* p<0.05, ** p<0.01, *** p<0.001"

Next, we obtain the estimated migration probabilities for each academic category/GPA/gender combination using the estimated model coefficients in column (f) and present results in Table 10.

Table 10. SSH: Female & Male cross-category Migration and Persistence Probabilities

	STEM			BE			SSH			OP			Drop		
SSH-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	1.9%	4.6%	2.7%	1.3%	4.0%	2.7%	82.9%	74.9%	-8.0%	5.4%	5.7%	0.3%	8.5%	10.9%	2.4%
2.5	1.4%	3.2%	1.8%	1.0%	2.9%	1.9%	87.4%	82.3%	-5.1%	4.0%	4.0%	0.0%	6.2%	7.6%	1.4%
3	1.0%	2.2%	1.2%	0.7%	2.0%	1.3%	90.9%	88.0%	-3.0%	2.9%	2.7%	-0.1%	4.5%	5.1%	0.6%
3.5	0.7%	1.5%	0.7%	0.5%	1.3%	0.8%	93.5%	92.0%	-1.5%	2.1%	1.8%	-0.2%	3.2%	3.4%	0.2%
4	0.5%	0.9%	0.4%	0.4%	0.9%	0.5%	95.4%	94.8%	-0.6%	1.5%	1.2%	-0.3%	2.3%	2.2%	-0.1%

We find that among SSH-starters, the persistence pattern is similar to BE-starters but reverse compared to that we saw among STEM-starters. Specifically, SSH-starting women display higher levels of persistence relative to their male counterparts at lower grade levels. Second, the observed gender differential widens as the grade received in SSH declines. Overall, the growing gender differential implies that men are relatively more responsive to the grades they receive in SSH. It is worth noting again that this is a category-specific phenomenon.

This surprising pattern is a combined result of the workings of two factors, according to the estimated regression coefficients. First, the estimates show that men place a higher weight on the taste for grade they receive in SSH (i.e., exhibit stronger "grade-sensitivity" according to the terminology we discussed in the Introduction) so that they are more responsive when the grade declines. Second, men "like" SSH less, i.e., have lower corresponding taste coefficient for the field, than do women. The first of the two factors is a novel finding of our analysis, which we are able to single out thanks to considering it in combination with the second one.

4.4 Analysis OP starters

We further estimate model (1) for OP-starters and present their estimation results in Table 11. Regarding the gender difference in taste toward different destination categories among OP-starting students, we find that OP-starting men "like" OP slightly more than their female counterparts do, but men "dislike" bad grade more strongly than women do. Both factors play an important role in the total gender gap in terms persistence. Moreover, surprisingly, among the OP-starters, men "like" all categories, including STEM, BE, SSH more than do women, relative to the dropout option. The interpretation of a somewhat surprising finding that OP-starting men have a stronger taste for it than do women is similar to the case of our analysis of BE-starter: men who self-selected to start in OP indeed do tend to have very strong taste for it.

Table 11. Estimation Results for OP Starters

	a	b	c	d	e	f
gpa_demean	0.986***	0.994***	0.985***	1.003***	0.806***	0.790***
	(0.0768)	(0.0936)	(0.0774)	(0.0982)	(0.109)	(0.110)
infor	0.535	0.543	0.697	0.680	0.154	0.202
	(0.484)	(0.486)	(0.483)	(0.486)	(0.498)	(0.500)
male_gpa		-0.0185		-0.0409	0.00451	0.0168
		(0.129)		(0.140)	(0.142)	(0.142)
STEM.male			0.643*	0.638*	0.632	0.572
			(0.324)	(0.324)	(0.344)	(0.344)
BE.male			1.271***	1.248***	1.228***	1.233***
			(0.323)	(0.332)	(0.348)	(0.351)
SSH.male			0.122	0.111	0.0520	0.0435
			(0.227)	(0.231)	(0.242)	(0.243)
OP.male			-0.0516	-0.0675	0.0582	0.0615
			(0.116)	(0.128)	(0.134)	(0.135)
Pre-college performance	N	N	N	N	Y	Y
Demographics	N	N	N	N	N	Y
N	38940	38940	38940	38940	38940	38940

Standard errors in parentheses; "* p<0.05, ** p<0.01, *** p<0.001"

Table 12 provides the distribution of destination academic categories for OP-starters. Here, we observe persistence patterns similar to BE and SSH-starting subpopulations where men are more responsive to the grade they received when they make decisions to persist in their current field.

Table 12. OP: Female & Male cross-category Migration and Persistence Probabilities

	STEM			BE			SSH			OP			Drop		
OP-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	1.3%	2.2%	1.6%	0.9%	2.9%	2.0%	3.7%	3.6%	-0.1%	83.0%	80.9%	-2.1%	11.0%	10.4%	-0.6%
2.5	1.0%	1.6%	1.3%	0.7%	2.1%	1.4%	2.7%	2.6%	-0.1%	87.9%	86.3%	-1.5%	7.9%	7.4%	-0.5%
3	0.7%	1.1%	1.2%	0.5%	1.5%	1.0%	1.9%	1.8%	0.0%	91.4%	90.4%	-1.1%	5.5%	5.2%	-0.3%
3.5	0.5%	0.8%	1.0%	0.3%	1.0%	0.7%	1.3%	1.3%	0.0%	94.1%	93.3%	-0.7%	3.9%	3.6%	-0.3%
4	0.3%	0.5%	0.9%	0.2%	0.7%	0.5%	0.9%	0.9%	0.0%	95.9%	95.4%	-0.5%	2.7%	2.5%	-0.2%

We further observe that for students deciding to exit their starting category, the popularity of a destination varies substantially by starting category and changes as the grade received declines; these changes, moreover, can differ between genders. According to gender differentials in the table, however, there are two features that remain consistent across the two academic categories presented. First, *OP-starting men are consistently more likely than women to migrate to STEM*. Second, *women are consistently more likely to migrate to SSH or dropout than men*. For this latter migration trend, it is also worth noting that the gender gap in migration widens as the grade received declines. In other words, women dominate the SSH destination migration pathway to an increasingly greater extent as the grade received declines.

4.5 Explanation

Overall, our empirical evidence demonstrates that women persist relatively more strongly in SSH, BE, and OP while men persist in STEM in a relatively greater proportion than women. This novel result shows that the phenomenon of relatively stronger responsiveness to grades exhibited by women in STEM (which we reported above and which is consistent with the existing literature focusing specifically on STEM) is in fact discipline-specific. Furthermore, the above analysis of gender differences in persistence and migration across academic disciplines challenges the *grade sensitivity-centered* conjecture commonly made in the literature that women generally respond more strongly to low grades than men in their decisions against persisting in an initially chosen field and that such female-specific characteristic is responsible for disproportionately driving women away from the disciplines that tend to assign lower grades.

Instead, we find that the gender difference in responsiveness to grades is not universal but is category-specific in magnitude and direction. Specifically, we find that men are more directly “sensitive” to grades than women in all four starting categories; however, their persistence patterns differ across categories because of the relative difference in their tastes toward them in each subpopulation: men "like" STEM more but SSH less than do women, respectively. In STEM, specifically, men's stronger preference toward STEM outweighs their greater disutility of low grade, resulting in their stronger persistence in STEM compared to women's.

Thus, from our analysis, the gender difference in the observed persistence patterns comes from two different sources: gender differences in students' taste directly towards grades and towards academic categories. Surprisingly and contrary to the conventional understanding, in each starting category, we find that men put more weight than women on the taste towards the grade they received. However, men do not respond more strongly than women when receiving a lower grade. This is because the decision about persisting in an academic category is affected, in addition to the taste for grades, by students' tastes for academic disciplines, so that the observed persistence patterns are combined results of the two factors.

5. Robustness Check: Gender Peer Effect

We perform two robustness checks of the previous section's baseline results on gender differences in persistence in and migration from students' starting (i.e., second-year) academic categories. One of the key baseline results is that men are relatively more persistent than women in STEM and that the gap grows as the grade received in STEM declines. There are two possible channels that could influence a persistence pattern like this. One is that decisions by female students whether to persist in a class may be affected by having too few female peers. In such a case, the initial underrepresentation of women in a field could itself contribute to their relatively lower persistence. In this section, we perform the check whether our results are robust to this gender peer effect.

Another factor that could influence our baseline results is a possibility is that students who plan to abandon their starting academic category but are still enrolled in some classes associated with it, will choose to complete the classes but devote low effort to them due to the change of plans. In such cases, students' weak performance in the starting academic category's classes would constitute "forfeiture", i.e., be caused by the decision to abandon the corresponding academic category, rather than serving as its cause. We demonstrate the robustness of our estimates and the persistence pattern overall to this phenomenon in the Appendix.

To control for the gender peer effect, we introduce a control for the gender ratio of each student's classroom experience within each academic category. Since gender composition varies across classes within each academic category, we calculate the gender ratio for each class a student takes in a given category, and then take the average of those ratios to create an aggregate measure representing the student's overall gender peer experience in the category up to the fourth semester. In other words, we create a course section-specific *gender ratio* variable for each academic category to capture each student's gender-peer experience within a category. The focus on course sections is of essence because many courses are offered in multiple sections per semester. The *gender ratio* variable used here reports the section-specific gender compositions for all sections of a relevant class in a given semester. This approach is essential as it accounts for the relevant gender composition directly experienced by affected students. Further, our *gender ratio* variable is tied to student's gender: if a student is male, the variable reports the proportion of males in the section, *mutatis mutandis*.

Table 13 presents the estimates of persistence and migration probabilities along with their

Table 13. Estimation Results for STEM, SSH, BE, and OP Starters

	STEM			BE			SSH			OP		
	d	e	f	d	e	f	d	e	f	d	e	f
gpa_demean	0.991***	0.833***	0.831***	0.958***	0.536***	0.536***	0.766***	0.471***	0.466***	0.728***	0.473***	0.456***
	(0.0746)	(0.0895)	(0.0900)	(0.0859)	(0.0908)	(0.0912)	(0.0576)	(0.0663)	(0.0664)	(0.0903)	(0.0999)	(0.100)
infor	2.647***	2.145***	2.146***	2.546***	1.228***	1.224***	0.875***	0.00544	0.0351	0.924**	0.220	0.250
	(0.290)	(0.342)	(0.344)	(0.285)	(0.295)	(0.296)	(0.201)	(0.223)	(0.224)	(0.328)	(0.348)	(0.350)
male_gpa	0.159	0.133	0.141	0.0176	0.0251	0.0187	0.178**	0.180**	0.186**	-0.0125	0.0244	0.0331
	(0.0853)	(0.0842)	(0.0849)	(0.0853)	(0.0848)	(0.0852)	(0.0644)	(0.0642)	(0.0641)	(0.110)	(0.112)	(0.113)
STEM.male	-0.0401	0.0617	0.0536	0.257	0.294	0.306	0.696***	0.659***	0.630**	0.568	0.602	0.544
	(0.142)	(0.149)	(0.150)	(0.301)	(0.308)	(0.309)	(0.184)	(0.193)	(0.194)	(0.324)	(0.343)	(0.344)
BE.male	0.771*	0.892*	0.892*	-0.509**	-0.367*	-0.396*	1.100***	1.102***	1.106***	1.273***	1.293***	1.317***
	(0.383)	(0.400)	(0.403)	(0.160)	(0.164)	(0.165)	(0.217)	(0.227)	(0.228)	(0.343)	(0.360)	(0.364)
SSH.male	-0.476*	-0.558*	-0.536*	-0.758**	-0.777**	-0.812**	-0.260**	-0.159	-0.174	0.0591	0.0286	0.0181
	(0.212)	(0.222)	(0.223)	(0.239)	(0.247)	(0.249)	(0.0863)	(0.0910)	(0.0911)	(0.228)	(0.239)	(0.240)
OP.male	-1.264***	- 1.145***	-1.172***	-0.652**	-0.616**	-0.677**	-0.219	-0.164	-0.193	-0.120	0.0264	0.0298
	(0.224)	(0.235)	(0.236)	(0.226)	(0.233)	(0.235)	(0.139)	(0.146)	(0.146)	(0.122)	(0.129)	(0.129)
Pre-college performance	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Demographics	N	N	Y	N	N	Y	N	N	Y	N	N	Y
N	33460	33460	33460	57475	57475	57475	63575	63575	63575	38940	38940	38940

Standard errors in parentheses; "* p<0.05, ** p<0.01, *** p<0.001" corresponding gender differentials, after controlling for the newly introduced *gender ratio*. From the estimates, we can see that the gender ratio is not statistically significant from zero for all specifications and all starting categories, which indicates that gender is not an important determinant when students decide their future categories.[20]

Thus, the trends of growing gender gaps in favor of men in persistence in STEM are preserved under this robustness check, albeit with minor moderation in the strength of the effect of declining GPA.

Table 14. Female & Male cross-category Migration and Persistence Probabilities

STEM-starters															
	STEM			BE			SSH			OP			Drop		
STEM-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	82.2%	86.1%	4.0%	1.0%	2.5%	1.5%	5.1%	3.4%	-1.8%	6.5%	2.2%	-4.3%	5.2%	5.8%	0.6%
2.5	87.4%	91.0%	3.5%	0.7%	1.6%	0.9%	3.6%	2.2%	-1.4%	4.6%	1.5%	-3.1%	3.6%	3.8%	0.1%
3	91.3%	94.2%	2.9%	0.5%	1.0%	0.6%	2.5%	1.4%	-1.1%	3.2%	0.9%	-2.2%	2.5%	2.4%	-0.1%
3.5	94.1%	96.4%	2.3%	0.3%	0.7%	0.3%	1.7%	0.9%	-0.8%	2.2%	0.6%	-1.6%	1.7%	1.5%	-0.2%
4	96.0%	97.7%	1.7%	0.2%	0.4%	0.2%	1.1%	0.6%	-0.6%	1.5%	0.4%	-1.1%	1.2%	0.9%	-0.2%
BE-starters															
	STEM			BE			SSH			OP			Drop		
BE-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	0.9%	1.8%	0.9%	91.1%	90.4%	-0.8%	2.4%	1.6%	-0.8%	2.9%	2.2%	-0.7%	2.7%	4.0%	1.3%
2.5	0.7%	1.4%	0.7%	93.0%	92.5%	-0.5%	1.9%	1.2%	-0.6%	2.3%	1.7%	-0.6%	2.1%	3.1%	1.0%
3	0.5%	1.1%	0.6%	94.5%	94.2%	-0.4%	1.4%	1.0%	-0.5%	1.8%	1.4%	-0.5%	1.6%	2.4%	0.8%
3.5	0.4%	0.9%	0.4%	95.7%	95.5%	-0.3%	1.1%	0.7%	-0.4%	1.4%	1.1%	-0.4%	1.3%	1.9%	0.6%
4	0.3%	0.7%	0.3%	96.7%	96.5%	-0.2%	0.9%	0.6%	-0.3%	1.1%	0.8%	-0.3%	1.0%	1.4%	0.4%
SSH-starters															
	STEM			BE			SSH			OP			Drop		
SSH-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	1.4%	3.6%	2.2%	1.0%	3.6%	2.6%	86.7%	79.1%	-7.6%	4.2%	4.6%	0.4%	6.7%	9.1%	2.4%
2.5	1.2%	2.8%	1.6%	0.8%	2.8%	2.0%	89.2%	83.9%	-5.3%	3.4%	3.6%	0.1%	5.4%	7.0%	1.5%
3	0.9%	2.1%	1.1%	0.6%	2.1%	1.5%	91.2%	87.8%	-3.4%	2.8%	2.7%	-0.1%	4.4%	5.3%	0.9%
3.5	0.8%	1.6%	0.8%	0.5%	1.6%	1.1%	92.9%	90.8%	-2.1%	2.3%	2.0%	-0.2%	3.6%	4.0%	0.4%
4	0.6%	1.2%	0.6%	0.4%	1.2%	0.8%	94.3%	93.2%	-1.1%	1.8%	1.5%	-0.3%	2.9%	2.9%	0.1%
OP-starters															
	STEM			BE			SSH			OP			Drop		
OP-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	0.8%	1.5%	0.6%	0.6%	2.2%	1.6%	2.5%	2.5%	0.0%	88.5%	86.3%	-2.2%	7.6%	7.6%	0.0%
2.5	0.7%	1.2%	0.5%	0.5%	1.7%	1.3%	2.0%	2.0%	0.0%	90.6%	88.9%	-1.7%	6.2%	6.1%	-0.1%
3	0.6%	0.9%	0.4%	0.4%	1.4%	1.0%	1.7%	1.6%	0.0%	92.3%	91.1%	-1.2%	5.1%	4.9%	-0.1%
3.5	0.5%	0.8%	0.3%	0.3%	1.1%	0.8%	1.3%	1.3%	0.0%	93.8%	92.9%	-0.9%	4.1%	3.9%	-0.2%
4	0.4%	0.6%	0.2%	0.3%	0.9%	0.6%	1.1%	1.0%	0.0%	95.0%	94.3%	-0.7%	3.3%	3.1%	-0.2%

[20] Our focus is on the persistence pattern after *controlling* for the peer effect, whereas the magnitude of the effect of gender peers *per se* was the subject of attention of Ost (2010) and Kugler et al (2017).

Our empirical analysis has revealed strong distinctions between groups of disciplines with respect to gender differences in the patterns of student persistence in and migration across academic categories. The theoretical model we develop in the next section is aimed at gaining insight into the mechanism underlying this newly uncovered phenomenon, i.e., to provide its micro-foundations. Our model features individual differences in the weights individuals attach to the taste for field-specific human capital and associated careers, which may correlate with gender (as observed in the empirical literature) and translates into differences in their degrees of attachment to corresponding academic disciplines. Additionally, students differ in their direct tastes for ("sensitivity" to) grades, while all being averse to study effort. The model is able to demonstrate that students' field-preferences is a deciding factor in their responsiveness to grades in a discipline, in terms of choosing and/or persisting in it. Furthermore, it provides stylized predictions remarkably consistent with the empirical patterns showing that gender differences in choices of and persistence in majors are not uniform but exhibit distinctions across the array of disciplines, as we have demonstrated here.

6. Trade-offs in choosing a college major: a theoretical framework

We structure this section as follows. First, in subsection 6.1, we present a model of student decisions about selecting and/or persisting in a field of study. Subsection 6.2 derives baseline results in the framework where students make college decisions at once, based on supposed complete information about their academic ability. Then, in subsection 6.3, we extend these results to the main case of interest where the college study consists of two stages, the lower and the upper division, whereby students learn about their ability upon completing the first stage based on grade performance there and then adjust their initial choices accordingly.

6.1. The model: decisions and tradeoffs under complete information

One can think of an individual college student's decision to choose an academic field and then either to persist in it or to switch to a different one in the spirit of Manski (1989) who analyzed sequential individual decisions about whether to enroll and then to persist in college. In such a utilitarian framework, students consider characteristics of a major, as well as their own individual characteristics, such as abilities and tastes.

To streamline the theoretical argument, we make a common simplification that student pre-college academic characteristics can be reduced to a single variable a of universal academic ability (pre-college preparation). We shall initially suppose that each *student i has advance perfect knowledge of his/her ability* (a_i and is thus able to make an informed choice of a college career. Upon obtaining the relevant results, we shall discard this assumption and let the initial choices be based on imprecise beliefs, which get updated in the course of studies, such that students may then change their *ex ante* choices accordingly.

We posit that while in college, each student *i* chooses to pursue one of its majors *m*=1,2,…,*M*. We denote as *m*=0 the option of not going to college, and let the corresponding level of welfare denoted by V_0 be fixed, i.e., not dependent on individual characteristics.

Thus, the human capital level college-bound individual *i* will choose to attain will be major-specific, hence denoted as $h_{m,i}$. We further assume that a student makes these educational choices to maximize her utility function, which depends positively on her taste for human capital attainment in a chosen major, decreases in the educational effort *e* it entails, and increases in psychic benefits of GPA grade *g* earned in college. Assuming separability for the simplicity of argument, the utility function of student *i* can be written as:

$$U_i = \alpha_{m,i} u(h_{m,i}) - v(e \mid a_i) + \gamma_i s(g) \tag{2}$$

where the first component represents student's taste for attributes of a major *m*, which may include both pecuniary and non-pecuniary characteristics of a career associated with it as well as the attributes of its academic content and depends on one's level of human capital attainment in the major, the second component captures the disutility of effort, and the third one accounts for the psychic benefits derived from receiving a high grade or the distress from a low grade. As will be detailed below, student's human capital attainment in college depends on the effort he or she chooses to exert; so does the grade earned. Note that all the components in expression (2) depend on student's ability since a given effort level produces superior outcomes when ability is higher. Coefficients $\alpha_{m,i}$ and γ_i stand for the weights student *i* attaches to the components of utility associated with the taste for human capital in a chosen major and the taste for (or "sensitivity" to) the GPA grade received, relative to the disutility associated with the effort involved. It is clear that both the taste for human capital in a major and the grades-driven component of utility create distinct incentives to exert more study effort in any major. However, whereas the effect of the grades-driven component is invariant to the chosen major, the effect of the taste for a major obviously differs across the majors, because they differ in the grading standards. Indeed, the preference for a less demanding major is aligned with obtaining higher grades, *ceteris paribus*, and thus can be observationally equivalent to stronger taste for (sensitivity to) grades. As we have shown in previous sections, estimating this distinction between taste for major-driven and sensitivity to grades-driven student choices allows one to differentiate the motivation behind students' decisions about major choices. Here, we aim to clarify this distinction by means of a theoretical analysis. As mentioned earlier, we assume, as is standard and realistic, that student *i*'s human capital attainment level in any major *m* she chooses is an increasing function of her ability and the effort she chooses to exert while pursuing the major. For simplicity but without loss of generality, we use the following common functional form:

$$h_{m,i} = a_i e_{m,i} \tag{3}$$

We further posit that each major establishes a grading scale such that the major-specific GPA grade of student *i* increases with her human capital attainment in the major, i.e., $g_m(h_{m,i})$ is a strictly increasing function. (Note that we consider GPA grade as a continuous variable, which is consistent with GPA measurement as well as this paper's empirical model.) Equivalently, each major establishes a *scale of its academic standards* corresponding to each grade level *g*, such that the strictly increasing function $h_m(g)$ is the level of attainment of human capital specific to major *m* required for obtaining grade *g* in the major. This implies that student's choice of human capital attainment in major *m* is equivalent to the choice of a grade level to pursue there. For a student of given ability, these choices are in turn equivalent, according to (3), to the student's choice of the level of effort to exert in pursuing major *m*.

To summarize, student's decisions in the model can be reduced to two choices: of major *m* and grade level *g* to pursue in it. As stated earlier, the choice of grade level *g* in major *m* is equivalent to choosing the level of human capital attainment $h_m(g)$. Thus, according to expression (3), student's utility maximization problem can be stated as

$$\max_{m,\,g}\; U_{m,i} = \alpha_{m,i} u(h_m(g)) - v\left(\frac{h_m(g)}{a_i}\right) + \gamma_i s(g) \tag{4}$$

As explained above, the problem can be equivalently formulated in terms of student's choice of major *m* and the level of educational effort e to exert in pursuing it, i.e.,

$$\max_{m,e} U_{m,i} = \alpha_{m,i} u(a_i e) - v(e) + \gamma_i s(g_m(a_i e)) \tag{5}$$

given student's level of ability a_i, which we assume to be distributed in a finite interval $[\underline{a}, \overline{a}]$.

We shall now analyze the tradeoffs a student of given *known* ability faces when choosing between some two majors, $m = k, j$. There is ample evidence (see, e.g., Aachen and Courant, 2009) that prevailing grade levels differ strongly across academic disciplines; for instance, they are markedly lower in STEM, higher in SSH. There is also empirical evidence that these grade comparisons are only strengthened when controlled for students' measured ability (see Arcidiacono, 2004, as well as, on Indiana University data, Kaganovich and Su, 2020). This then implies a difference in academic standards, i.e., the fact that some majors impose higher requirements in comparable study effort for a given grade, than do others. Based on this evidence, we assume here that major *k* has higher standards than major *j*, such that for each grade level *g* the corresponding academic standards for achieving this grade, $h_k(g)$ and $h_j(g)$ satisfy $h_k(g) > h_j(g)$. This then implies that attaining a particular grade level in major *k* will take a student of given ability more effort than in major *j*. Furthermore, for the purposes of this analysis we make a stronger simplifying assumption that for a student of given ability, the level of effort required in major *k* is higher than that in major *j*, regardless of the grades pursued there[21] and formulate this as the following condition.

<u>Assumption 1</u>: The academic standards in t major *k* strongly dominate those of major *j*. That is, for any grade levels g_k and g_j in the respective majors, the corresponding academic standards compare as follows: $h_k(g_k) > h_j(g_j)$.

Assumption 1 directly implies that, controlling for individual ability *a*, a student would need to

[21] Babcock and Marks (2011) document that study time is persistently the highest on average (without controlling for ability) in engineering and sciences. Kaganovich and Su (2020) consider a model where career income is the only attribute of a major that matters to students and show that if the difference in wage rates between majors is substantial enough, this leads to the "separated" majors outcome, where academic standard even for attaining a low passing grade in the more lucrative major exceeds the standards for any grade in the less lucrative one. They present empirical evidence of a trade-off between career earnings associated with college majors and prevailing grades (hence higher grading standards in more lucrative majors). They develop an explanation of this phenomenon through a model of intra-university competition between two majors where the academic standards for grades are used by departments strategically for attracting or deterring students, depending on academic eligibility. This leads to student self-sorting across departments, and, in equilibrium, to a positive relationship between job market rewards of majors and their grading standards.

exert higher effort if pursuing major k vs. that in major j. It is clear, that the "no college" option m=0 is the least academically "demanding" of all, requiring zero study effort, $e_0(a) \equiv 0$.

Assuming that functions u(.) and s(.) are concave while the disutility of effort v(.) is convex, problems (4) and (5) satisfy requisite sufficient conditions of optimality. The first order conditions then imply the following result, proven in detail in the Appendix, where we abandon for brevity student indexation i.

Lemma: Under the provisions of Assumption 1, there are threshold ability levels

$$a_{k/j} = a_{k/j}(\alpha_k, \alpha_j, \gamma), \quad a_{j/0} = a_{j/0}(\alpha_j, \gamma), \quad a_{k/0} = a_{k/0}(\alpha_k, \gamma) \tag{6}$$

such that, for a given set of utility weight coefficients $\alpha_k, \alpha_j, \gamma$, students with ability below a threshold will prefer the less demanding of the two options for which the threshold is defined, while students with ability above it will prefer the more demanding option in the binary choice.

Let $V_m(a, \alpha_m, \gamma)$ stand for the value function of the problem of maximizing the utility function U_m by a student of ability level a and weight coefficients $\alpha_k, \alpha_j, \gamma$ within major m:

$$V_m(a, \alpha_m, \gamma) = \max_e \ \alpha_m u(ae) - v(e) + \gamma s(g_m(ae)) \tag{7}$$

i.e., the highest level of welfare the student can achieve were he/she to pursue major m. Then the cut-off ability level $a_{k/j}$ obviously satisfies equality

$$V_k(a_{k/j}, \alpha_{k,i}, \gamma) = V_j(a_{k,j}, \alpha_{j,i}, \gamma)$$

It is then straightforward (see Appendix for details) to derive from Lemma 1 the following comparative statics result:

Proposition 1: The ability threshold $a_{k/j}$ for choosing more demanding major k over the less demanding j relates to student preference parameters as follows:

(i) it declines in the weight α_k a student places on her taste for human capital associated with the more demanding major k, given the weights she places on required effort, grades received, and her taste for the less demanding major j;

(ii) it increases in the weight α_j a student places on her taste for human capital associated with the less demanding major j, given the weights she places on required effort, grades received, and her taste for the more demanding major k;

(iii) it increases in students' direct sensitivity to grades γ, given the values of her taste for majors' coefficients, subject to an additional parametric condition that the preference coefficients α_k and α_j associated with the taste for educational benefits of majors are large relative to the weight given to the disutility of effort (which was normalized to 1).[22]

Proposition 1 results (i) and (ii) compare students who differ in their values of weights α_k or α_j, respectively, in utility function (5) but do not differ in their taste for the alternative major or in coefficient γ, the direct sensitivity to grades.

Result (i) implies, in this stylized analytical framework, that the more students value the benefits derived from a more demanding major*, the more strongly the ability sorting among them will be biased in favor of this major*, such that this major will then attract additional less able such students who will be therefore putting up with higher effort and lower grades. This then implies a *trade-off between the coefficient* α_k, the taste for more demanding major, *and the grade level acceptable to a student*. Specifically, the higher the weight α_k a student of given ability attaches to her direct utility of (taste for) the demanding major, the lower is the acceptable grade level, at which she will still prefer to choose this major. Therefore, students whose preferences feature higher weight α_k will be willing to accept relatively lower grades in the major, rather than choosing the alternative, less demanding, major in exchange for better grades, compared to their peers. Thus, such students will exhibit behavior observationally equivalent to lower direct sensitivity to grades, without this being the case. In a similar vein, result (ii) of the Proposition means that the stronger students' preferences for human capital in less demanding major, the less willing, *ceteris paribus*, they will be to accept higher effort and lower grades associated with more demanding major. *Such students will thus exhibit behavior observationally equivalent to higher direct sensitivity to grades, without this necessarily being the case*. Finally, Proposition 1(iii) considers the direct effect of sensitivity to grades in student preferences. It shows that, other things equal, ability sorting among students with a higher γ, i.e., those whose preferences

[22] See the Proposition's proof in the Appendix for detailed formulation of this parametric condition. It ensures that for a student indifferent between the two majors, the loss of educational benefit associated with less demanding one is not fully compensated by the gains from the reduced study effort there. This implies that to be rational, the choice of less demanding major requires an additional compensation of a higher grade. The purpose of the parametric condition is to ensure the effective compensatory role of more generous grading policy in the less demanding major.

feature stronger direct "sensitivity" to grades, will be (not surprisingly) *more strongly biased in favor of a less demanding major*. In other words, the higher the weight a student of given ability attaches to the benefits of better grades, the less willing the student will be to accept lower grades associated with the more demanding major. That is, such student will only choose more demanding major subject to receiving a relatively "less bad" grade there than would be acceptable to a student with a lower value of coefficient γ .

The juxtaposition of results (i-ii) vs. (iii) of the Proposition thus represent two possible alternative explanations for observed differences between individual students and groups of students in their responses to grades when choosing between academic disciplines: one based on differences in unconditional direct sensitivity to grades *per se*, the other more nuanced where revealed responsiveness to grades received in a major is derived from a student's preferential attachment to it. The approach to explaining systematic gender differences in the choices of and/or persistence in college majors proceeds from the assumption of differences in "sensitivity" to grades γ as an exogenous characteristic of students' preferences is standard in the literature we surveyed in the Introduction, which tends to assign such superior systematic "sensitivity" to women. Such explanation can be supported, in principle, by Proposition 1(iii) which shows that students with higher exogenous sensitivity to grades γ will gravitate more, *ceteris paribus*, toward the less demanding major. It is not hard to see, however, that Proposition 1(iii) also implies that the gender biases in the aggregate responsiveness to their grades would be similarly systematic across fields. This is contradicted by our findings that men are at least no more tolerant of lower grades than are women in STEM and SSH. Indeed, Proposition 1(i) shows that if men have stronger interest in a more demanding major (like STEM) than women, they will then exhibit less responsiveness to low grades than women in this major (in terms of persistence there) even if they have equal or stronger direct preferential sensitivity to grades than women.

Likewise, according to Proposition 1(ii), if women happen to have stronger interest in a less demanding major (like SSH) than men, they will exhibit more tolerance for low grades in it than men even if their direct sensitivity to grades is weaker than men's.

These theoretical results are particularly essential for explaining the distinction between the gender effects we demonstrated in BE vs. STEM, both relatively demanding academic fields. Indeed, whereas these distinctions would be hard to explain based on the hypothesis of women's inherent higher direct sensitivity to grades, estimation of our econometric model shows that they are explained by the variation of academic category-specific tastes across genders.

We shall now bring together the above analysis of tradeoffs in the choice between college majors with the additional "no college" option *m*=0. To simplify the argument, we assume that preference parameters $\alpha_k, \alpha_j, \gamma$ can take on only two distinct values each in the population, high and low, for instance α_k^H and α_k^L. The population of (potential) students thus breaks into eight discrete groups characterized by different combinations of the corresponding parameter values. We assume that these differences between the groups are uncorrelated with academic ability, which equally varies in both groups. Consider, for instance groups A and B, characterized by parameter values $\alpha_k^H, \alpha_j^N, \gamma^N$ and $\alpha_k^L, \alpha_j^N, \gamma^N$, respectively, where $N=H,L$. Thus, group A individuals have stronger inherent preference for the more demanding major than individuals in group B, whereas members of the two groups have similar tastes for major *j* and for grades. Since welfare level associated with not going to college V_0 does not depend on ability, the results of Lemma extended to the option of "no college" imply that for students in group A <u>with sufficiently high ability</u> the following welfare ranking of the options obtains:

$$V_k(a, \alpha_k^H, \alpha_j^N, \gamma^N) > V_j(a, \alpha_k^H, \alpha_j^N, \gamma^N) > V_0 \tag{8}$$

because according to Proposition 1(i) the ability threshold $a_{k/j}(\alpha_k^H, \alpha_j^N, \gamma^N)$ above which individuals prefer major k over major j, is relatively low.

Also according to Proposition 1(i), the threshold ability level $a_{k/j}(\alpha_k^L, \alpha_j^N, \gamma^N)$ is relatively high. Therefore, for students in group B (who have weaker taste for the major *k*) with ability that is sufficiently high but below the threshold: $a < a_{k/j}(\alpha_k^L, \alpha_j^N, \gamma^N)$, the welfare ranking of the options will contrast with the above:[23]

$$V_j(a, \alpha_k^L, \alpha_j^N, \gamma^N) > V_k(a, \alpha_k^L, \alpha_j^N, \gamma^N) > V_0 \tag{9}$$

The direct comparisons of the expressions for welfare functions clearly imply that the best choice for individuals of sufficiently low ability in either group A and B is "no college", i.e., welfare

[23] Inequalities (8) and (9) impose implicit but standard conditions on the magnitude of welfare level V_0 given by the "no college" option and the range of abilities to ensure that the college-bound population is not empty, and neither is the population of those who are better off without a college degree.

level V_0 dominates the alternatives.

Therefore, it is not hard to see, based on the Lemma, that tracing the welfare comparisons while reducing student ability levels from those corresponding to the respective welfare rankings (8) and (9) toward low levels where "no college" option dominates, lead to the following results.

Proposition 2. Consider, groups of individuals A and B, characterized by parameter values $\alpha_k^H, \alpha_j^N, \gamma^N$ and $\alpha_k^L, \alpha_j^N, \gamma^N$, respectively, where *N=H, L*. Thus, group A individuals have strong inherent taste for the more demanding major *k* than members of group B, whereas they do not differ in their other taste parameters. Then the group-specific ability thresholds, which determine individual preferences between the corresponding options, satisfy the following relationships:

(i) $a_{j/0}(\alpha_k^H, \alpha_j^N, \gamma^N) > a_{k/0}(\alpha_k^H, \alpha_j^N, \gamma^N) > a_{k/j}(\alpha_k^H, \alpha_j^N, \gamma^N)$,

which implies that the group A of individuals who more strongly value the benefits of more demanding major *k* partitions into two sub-groups as follows. For all those with ability above $a_{k/0}(\alpha_k^H, \alpha_j^N, \gamma^N)$, pursuing major *k* is the top choice. For those whose ability falls below this threshold, the "no college" option dominates all else, including the option of graduating with the less demanding major *j*.

(ii) $a(k, j \mid \alpha_k^L, \alpha_j^N, \gamma^N) > a(k, 0 \mid \alpha_k^L, \alpha_j^N, \gamma^N) > a(j, 0 \mid \alpha_k^L, \alpha_j^N, \gamma^N)$,

which means that the group of individuals with weaker taste for the benefits of major *k* partitions into the following three sub-groups. For those with ability $a > a_{k/j}(\alpha_k^L, \alpha_j^N, \gamma^N)$, pursuing major *k* in college is the top option. For those whose ability falls into the interval $a_{j/0}(\alpha_k^L, \alpha_j^N, \gamma^N) < a < a_{k/j}(\alpha_k^L, \alpha_j^N, \gamma^N)$, pursuing less lucrative major *j* is the best choice. Finally, for those with ability below the lower threshold, "no college" is the best option.

The main takeaway from Proposition 2 is that individuals who value the benefits of the more demanding major *k* sufficiently strongly but whose ability is not high enough to pursue it will prefer to not attend college over doing so with the other major *j*. This complements the findings of Proposition 1(i) that, other things equal, ability sorting in favor of demanding major *k* is stronger the weaker is students' taste for it.

6.2. Two-Stage College Scenario: Persistence and Migration Decisions

Recall that the analysis in the previous subsection proceeded under our initial simplifying scenario that students make the college enrollment and major choice decisions as a one-shot deal given complete information about their academic ability. The results we obtained are, however, applicable in the framework of this paper's empirical analysis, where *students had made their initial decisions under incomplete information* about their ability, and then, mid-way through college, once ability is revealed based on the first-stage academic performance, students can make adjustments. Thus, at this point in their studies, students are faced with an *ex post* choice between a new set of alternatives.[24]

We therefore now consider the following two-stage scenario, similar to our empirical framework. We consider students who chose to matriculate at college and to pursue a particular major *ex ante*, according to beliefs about their academic ability they had initially. These initial decisions are taken as given. Having completed the first stage of studies, these students have been able to infer their true academic ability based on performance there embodied in grades according to expression (3), and are now contemplating their choices *ex post*, in transition to the second, "upper division" stage of college education.

Specifically, let's consider a student who matriculated in college and initially chose a major based on the belief he/she had at the time that his/her ability level was a^0. Assume further, for the sake of argument, that based on this information the student chose the more demanding major *k* over major *j*. In the notation of Lemma, this implies that $a^0 > a_{k/j}(\alpha_k, \alpha_j, \gamma)$ assuming that the weight coefficients in the student's utility function (1) are given by $\alpha_k, \alpha_j, \gamma$. Suppose further that in the course of studies the student learns, based on GPA grades received, that his/her true ability level is lower: $a' < a^0$. The student faces three potential choices: (a) "persist" in the originally chosen major *k*, (b) switch to less demanding *j*, and (c) drop out of college.

The updated information about ability will compel the student to choose option (a), to persist in major *k*, if the updated ability level is high enough to "beat" both alternatives to it: switching to major *j* or dropping out of college. According to Proposition 2, this will be the case iff

$$a' > \max\left\{a_{k/j}(\alpha_k, \alpha_j, \gamma),\ a_{k/0}(\alpha_k, \alpha_j, \gamma)\right\}$$

[24] We will apply the results of Lemma and Proposition 2 to the *ex post* student decisions without accounting for the facts that the costs and benefits of continuing in college until graduation, or not, are not the same as the respective costs and benefits are at the point of college matriculation. This simplification helps streamline our exposition but does not diminish generality, since adjusting the analysis to the changes in the benefits and costs is straightforward.

If, however, the updated ability level falls below this threshold, Proposition 2 gives guidance for further analysis to determine, which of the alternatives, (b) or (c), prevails. According to Proposition 2, this depends on the taste α_k the student has for the benefits associated with human capital obtained in major *k*. This is so due to the result of Proposition 1 that threshold $a_{k/j}(\alpha_k, \alpha_j, \gamma)$ decreases in the coefficient α_k, such that

$$a_{k/j}(\alpha_k^H, \alpha_j, \gamma) < a_{k/j}(\alpha_k^L, \alpha_j, \gamma) \tag{10}$$

So, when the taste is strong, $\alpha_k = \alpha_k^H$, the threshold $a_{k/j}(\alpha_k^H, \alpha_j, \gamma)$ is low and, as stated in Proposition 2(i), is below $a_{k/0}(\alpha_k^H, \alpha_j, \gamma)$, such that

$$\max\left\{a_{k/j}(\alpha_k^H, \alpha_j, \gamma),\ a_{k/0}(\alpha_k^H, \alpha_j, \gamma)\right\} = a_{k/0}(\alpha_k^H, \alpha_j, \gamma) \tag{11}$$

This means that if the updated ability a' falls below this threshold, dropping out of college becomes the best option, rather than switching to the "easier" major *j*.

Along similar lines, Proposition 2(ii) shows that when the taste for major $k\alpha$ is low: $\alpha_k = \alpha_k^L$, then $a_{k/j}(\alpha_k^L, \alpha_j, \gamma)$ is relatively large, so

$$\max\left\{a_{k/j}(\alpha_k^L, \alpha_j, \gamma),\ a_{k/0}(\alpha_k^L, \alpha_j, \gamma)\right\} = a_{k/j}(\alpha_k^L, \alpha_j, \gamma) \tag{12}$$

and therefore, if the updated ability a' falls just below this threshold, then switching to major j is a better option than dropping out. The latter option becomes dominant only for students with substantially lower realizations: $a' < a_{j/0}(\alpha_k^L, \alpha_j, \gamma)$.

Furthermore, since ability threshold $a_{k/0}(\alpha_k, \alpha_j, \gamma)$ declines in α_k, we can write:

$$a_{k/0}(\alpha_k^H, \alpha_j, \gamma) < a_{k/0}(\alpha_k^L, \alpha_j, \gamma) \tag{13}$$

which, combined with (11) and (12), yields:

$$a_{k/0}(\alpha_k^H, \alpha_j, \gamma) < a_{k/j}(\alpha_k^L, \alpha_j, \gamma) \tag{14}$$

This means that the ability threshold for persisting in the demanding major *k* is lower for students who have stronger taste α_k for it.

We summarize the results of the above analysis as the following:

Corollary. Consider a student who was enrolled in the demanding major *k* based on the original estimate of academic ability a^0. If the student receives a downgraded signal of her ability $a' < a^0$ through a GPA grade received in the course of studies, the menu of actions she will take depends on the strength α_k of her taste for the major. The taxonomy of the possibilities is as follows.

(i) If the taste for major *k* is relatively strong, $\alpha_k = \alpha_k^H$, i.e., such that the ability threshold for major *j* becoming preferable to major k is sufficiently low:

$$a_{k/j}(\alpha_k^H, \alpha_j, \gamma) < a_{k/0}(\alpha_k^H, \alpha_j, \gamma) \tag{15}$$

then only the following two outcomes apply depending on the student's ability realization:

- the student will choose to persist in major *k* if $a' > a_{k/0}(\alpha_k^H, \alpha_j, \gamma)$;
- the student will choose to drop out of college if $a' < a_{k/0}(\alpha_k^H, \alpha_j, \gamma)$.

(ii) If the taste for the major is relatively weak, $\alpha_k = \alpha_k^L$, such that the opposite of inequality (15) holds, then the following three outcomes apply depending on the student's ability realization:

- the student will choose to persist in major k, if $a' > a_{k/j}(\alpha_k^L, \alpha_j, \gamma)$;
- the student will choose to switch to major j, if $a_{j/0}(\alpha_k^L, \alpha_j, \gamma) < a' < a_{k/j}(\alpha_k^L, \alpha_j, \gamma)$;
- the student will choose to drop out of college if $a' < a_{j/0}(\alpha_k^L, \alpha_j, \gamma)$.

(iii) Ability threshold for persisting in major *k* is lower for students with $\alpha_k = \alpha_k^H$ than those with $\alpha_k = \alpha_k^L$. Therefore there is an interval of updated ability levels $a' < a^0$, under which students from the former group will persist in major *k* whereas students from the latter group will abandon it. Thus other things (including direct sensitivity to grades) equal, students with higher taste for the major will exhibit stronger persistence in it.

It now remains to observe that the results of the Corollary fit remarkably well with the patterns of gender differences demonstrated in our empirical analysis in terms of explaining revealed responsiveness to grades received in a major by a student's preferential attachment to it rather than simply due to exogenous sensitivity to grades. Specifically, our empirical results had shown stronger persistence of men in STEM despite stronger direct sensitivity to grades they exhibit there This is due to men's higher taste for this academic area, which is able to override the opposite gap in grade sensitivity. When it comes to students starting in BE, also a demanding area, we found that women exhibit relatively stronger persistence, which is due to their higher taste for the discipline along with similar level of sensitivity to grades there as on the part of men. Again, these empirical results are well-explained by the theoretical ones in the Corollary and would have presented a puzzle based on the premise of direct "grade-sensitivity".

Our empirical results for SSH-starters showing that women's stronger persistence there despite the demonstrated weaker sensitivity to grades in this category compared to men's can be likewise explained following an analysis similar to the Corollary's applied to students who started out in a less demanding field. It implies that women's stronger taste for a field, as they are found to have for SSH, can override the other gender's stronger sensitivity to grades in it.

7. Concluding Comments

Our results affirm that male students exhibit significantly stronger persistence than women, *ceteris paribus*, in STEM disciplines, and that this gender differential is the strongest among students receiving low grades there. We also found that, among students starting but not persisting in STEM, women dominate in migration to SSH and OP, and that this dominance, again, strengthens as grades decline. These results appear consistent with what the literature has characterized as stronger "grade sensitivity" among women.

We were, however, able to demonstrate that this pattern does not extend to other disciplines. It is women who exhibit superior persistence among SSH- and OP-starters, and the gap strengthens as grades decline. These results are qualitatively true also for BE-starters, albeit with smaller gender gaps. These somewhat unexpected results are, to our knowledge, novel contributions to the literature on the subject, owing to the rich IU Learning Analytics data, which allowed us to look at student migrations across the whole spectrum of disciplines, whereas the existing literature primarily focused on persistence in STEM alone. Importantly, these new results also challenge the conventional explanation of women's inferior persistence in STEM and the facts of their predominance in migrating to more generously grading disciplines based on women's stronger "grade-sensitivity", interpreted as lower tolerance for bad grades *per se*. We have advanced and successfully tested an explanation that reconciles diverging gender differentials across different disciplines. Our main thesis is that stronger responsiveness to grades, rather than being a gender-specific phenomenon universal across academic fields, is more likely to reflect gender differences in students' underlying tastes for academic fields, whose existence in principle has been documented in the literature. According to this argument, contrary to a commonly suggested understanding that a student's ingrained stronger "grade-sensitivity" makes her/him less attached to academic disciplines known to assign lower grades, it is a student's weaker taste toward a field of study that is likely to make her/him more "sensitive" to grades received in it.

Our econometric analysis specifically estimates male and female students' comparative tastes for their academic disciplines as well as their tastes for grades received in them. We are then able to demonstrate that the empirical facts of differential gender patterns in persistence in disciplines and migration to academic alternatives are consistent with the model by being produced as combined results of students' decisions based on their taste-based evaluations of fields and grades which come with them.

While studying the factors behind student persistence in or attrition from a starting academic category, we focused on student migrations to alternative academic categories. We also documented student choices to drop out from IU entirely as an available option when not persisting in a starting discipline. Although detailed analysis of the factors determining students' decisions to drop out goes beyond the scope of this study, it does offer insights for fruitful novel lines of inquiry into students' dropout decisions. As articulated by Manski (1989), a decision to drop out reflects a student's assessment that his/her expected welfare value of the outside options is superior to that associated with persisting in college given the student's performance. The task of modeling student valuations of alternative options available to them can clearly be carried out in the framework of our econometric analysis, factoring in the discipline and grade components of student preferences, relative to the dropout option. For instance, a student pursuing STEM or BE and receiving poor grades there, is more likely to decide to drop out rather than switch to "softer" alternatives, if he/she attaches low combined welfare values to the latter and expected grades there. The insights developed in this paper allow us to conjecture, in particular, that men who perform poorly in STEM or BE, enough to decide to exit these disciplines, are more likely to drop out of the university rather than switch to an academic alternative such as SSH, relative to comparable women, controlling for other relevant characteristics.

Appendix

This Appendix has three sections. Section 1 provide supplemental materials: the lists of units (schools, departments, or programs) in each academic category and descriptive statistics characterizing student population, Section 2 presents the results of the "forfeiture" robustness check, and Section 3 provides the proofs of the key results stated in Section 6 of the paper.

1. Supplemental materials

Table A1. Academic Units Included in Academic Categories

STEM: Animal Behavior, Astronomy, Biochemistry, Biology, Biotechnology, Chemistry, Computer Science, Data Science, Earth and Atmospheric Sciences, Human Biology, Informatics, Intelligent Systems Engineering, Mathematics, Molecular Life Sciences, Medical Sciences, Neuroscience, Physics, Optometric Technology, Vision Science, Statistics.
Business and Economics: Business School, Economics Department
SSH: African American and African Diaspora Studies, American Studies, Anthropology, Art History, Central Eurasian Studies, Classical Studies, Comparative Literature, Criminal Justice, East Asian Languages and Cultures, English, European Studies, Folklore and Ethnomusicology, French and Italian, Geography, Gender Studies, History, History and Philosophy of Science, International Studies, Latin American Studies, Latino Studies, Linguistics, Medieval Studies, Media School, Music, Near Eastern Languages and Cultures, Philosophy, Political Science, Psychology, Russian and East European Institute, Religious Studies, Southeast Asian Studies, Slavic and East European Languages and Cultures, Sociology, Spanish and Portuguese, Theatre, Drama and Contemporary Dance, Victorian Studies.
OP: Art and Design, Nursing, Optometry, Public and Environmental Affairs, Public Health, Social Work.
Education: School of Education.

Table A2. Summary Statistics

	STEM		BE		SSH		OP	
	mean	sd	mean	sd	mean	sd	mean	sd
Male	0.571	0.495	0.701	0.458	0.390	0.488	0.315	0.465
White	0.785	0.411	0.857	0.350	0.839	0.367	0.846	0.361
first_generation	0.113	0.317	0.060	0.238	0.098	0.298	0.133	0.339
pell_grant_eligibility	0.190	0.392	0.092	0.288	0.191	0.393	0.210	0.407
residency	0.845	0.362	0.466	0.499	0.637	0.481	0.709	0.454
entry_gpa	3.221	0.609	3.286	0.534	3.160	0.621	3.050	0.592
SAT.math	646	77	659	70	605	74	586	67
SAT.verbal	656	82	659	78	656	83	613	81
STEM_gpa	2.931	0.726	3.013	0.762	2.306	1.200	2.517	0.956
BE_gpa	0.954	1.475	3.167	0.594	0.835	1.340	1.247	1.428
SSH_gpa	3.354	0.568	3.359	0.533	3.235	0.569	3.135	0.553
OP_gpa	2.923	1.515	2.600	1.684	2.551	1.644	3.427	0.466
STEM.InfoAbsent	0.000	0.000	0.009	0.097	0.125	0.331	0.046	0.209
BE.InfoAbsent	0.684	0.465	0.000	0.000	0.688	0.463	0.525	0.499
SSH.InfoAbsent	0.001	0.027	0.003	0.057	0.000	0.000	0.000	0.016
OP.InfoAbsent	0.195	0.396	0.280	0.449	0.270	0.444	0.000	0.000
STEM_gender_ratio	0.538	0.086	0.542	0.089	0.532	0.106	0.545	0.109
BE_gender_ratio	0.532	0.101	0.573	0.128	0.519	0.115	0.520	0.116
SSH_gender_ratio	0.549	0.085	0.548	0.080	0.576	0.085	0.562	0.075
OP_gender_ratio	0.612	0.171	0.622	0.168	0.627	0.179	0.643	0.152
Observations	6692		11495		12714		7788	

2. 'Forfeiture' Robustness Check

This robustness check briefly discussed in Section 5 of the paper addresses the possibility that students, who plan to abandon their starting academic category but are still enrolled in some classes associated with it, will choose to complete the classes but devote low effort to them due to the change of plans. In such cases, students' weak performance in the starting academic category's classes would constitute "forfeiture", i.e., be caused by the decision to abandon the corresponding academic category, rather than serving as its cause.

To address this possibility, rather than including students' performance in their last semester (i.e., second semester of the second year, fourth semester overall) of being registered in the starting academic category in the calculation of their cumulative GPA, we now use instead of it the cumulative GPA information up until but not including this last semester as a regressor. The rationale for this approach is that students' fourth semester academic performance in their starting academic category, if it immediately precedes the switch to an academic alternative, may be a consequence of having already decided to abandon the starting academic category. In other words, weak grade performance may be a consequence of a decision to leave the academic category and thus losing motivation to exert more effort, rather than the other way around, i.e., weak performance in the last semester causing the departure.

Using the cumulative grade information without including the fourth semester's grades, as described above, while keeping the rest of the covariates unchanged, we re-run the regression and produce new estimates in the following Table A3.

Table A3. Estimation Results for STEM, SSH, BE, and OP Starters

	STEM			BE			SSH			OP		
	d	e	f	d	e	f	d	e	f	d	e	f
gpa_demean	1.045***	0.887***	0.888***	0.841***	0.423***	0.419***	0.967***	0.753***	0.742***	1.001***	0.804***	0.788***
	(0.0871)	(0.101)	(0.102)	(0.119)	(0.123)	(0.123)	(0.0649)	(0.0738)	(0.0740)	(0.0982)	(0.109)	(0.110)
infor	1.050*	0.654	0.671	0.102	-1.159	-1.168	0.00595	-0.579	-0.560	0.686	0.183	0.204
	(0.454)	(0.486)	(0.489)	(0.683)	(0.695)	(0.697)	(0.302)	(0.317)	(0.319)	(0.510)	(0.521)	(0.523)
male_gpa	0.267*	0.265*	0.277*	0.226	0.249	0.249	0.143	0.169*	0.180*	-0.0391	0.00609	0.0184
	(0.111)	(0.112)	(0.113)	(0.132)	(0.132)	(0.132)	(0.0822)	(0.0828)	(0.0829)	(0.140)	(0.142)	(0.142)
gender_ratio	-0.442	-0.408	-0.399	-0.670	-0.589	-0.613	-0.117	-0.121	-0.144	0.0199	0.0654	0.0143
	(0.372)	(0.373)	(0.375)	(0.379)	(0.393)	(0.394)	(0.244)	(0.248)	(0.249)	(0.302)	(0.306)	(0.309)
STEM.male	0.0344	0.134	0.131	0.332	0.369	0.386	0.727***	0.669***	0.640***	0.636*	0.633	0.571
	(0.148)	(0.155)	(0.157)	(0.306)	(0.312)	(0.313)	(0.184)	(0.194)	(0.194)	(0.324)	(0.344)	(0.344)
BE.male	0.482	0.664	0.645	-0.299	-0.178	-0.198	0.966***	0.972***	0.981***	1.243***	1.217***	1.228***
	(0.368)	(0.383)	(0.386)	(0.188)	(0.194)	(0.194)	(0.211)	(0.221)	(0.222)	(0.335)	(0.351)	(0.354)
SSH.male	-0.440*	-0.520*	-0.495*	-0.755**	-0.758**	-0.794**	-0.206*	-0.113	-0.127	0.113	0.0563	0.0444
	(0.214)	(0.224)	(0.225)	(0.239)	(0.247)	(0.249)	(0.0910)	(0.0956)	(0.0957)	(0.232)	(0.243)	(0.243)
OP.male	-1.216***	-1.104***	-1.131***	-0.603**	-0.573*	-0.626**	-0.193	-0.151	-0.184	-0.0599	0.0695	0.0674
	(0.225)	(0.235)	(0.236)	(0.224)	(0.233)	(0.234)	(0.139)	(0.146)	(0.146)	(0.131)	(0.138)	(0.138)
Pre-college performance	N	Y	Y	N	Y	Y	N	Y	Y	N	Y	Y
Demographics	N	N	Y	N	N	Y	N	N	Y	N	N	Y
N	33320	33320	33320	57315	57315	57315	62970	62970	62970	38780	38780	38780

Standard errors in parentheses; "* p<0.05, ** p<0.01, *** p<0.001"

We can see that the estimates for both coefficients are quite robust for all starting categories. We then calculate the pattern of students' category decisions and provide the results in Table 16, which only differ slightly in magnitudes from the baseline estimates of Tables 6, 8, 10 and 12 (which had no gender peer effect controls), the overall persistence and migration trends remain. Specifically, the persistence and migration patterns are preserved even after we control for the reversed causality between decisions whether to persist in a category and the level of grades received there. We also observe, similarly to the case of the gender peer robustness check, that the forfeiture factor tends to magnify, albeit modestly, the negative effect of poor grades on students' likelihood to persist in their starting academic categories. Specifically, the results presented in Table 16 shows that male students remain more likely to persist in or migrate to STEM than their female counterparts; this persistence pattern holds true across all GPA ranges; the gender differential in persistence in favor of men in these categories continues to grow as the grade received declines.

Table A4. Female & Male cross-category Migration and Persistence Probabilities

STEM-starters															
	STEM			BE			SSH			OP			Drop		
STEM-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	81.6%	85.1%	3.5%	1.2%	2.5%	1.3%	5.4%	3.8%	-1.6%	6.5%	2.5%	-4.0%	5.3%	6.1%	0.8%
2.5	87.3%	91.0%	3.7%	0.8%	1.5%	0.7%	3.7%	2.3%	-1.4%	4.5%	1.5%	-3.0%	3.7%	3.6%	0.0%
3	91.4%	94.8%	3.3%	0.6%	0.9%	0.4%	2.5%	1.3%	-1.2%	3.0%	0.9%	-2.2%	2.5%	2.1%	-0.3%
3.5	94.3%	97.0%	2.7%	0.4%	0.5%	0.2%	1.7%	0.8%	-0.9%	2.0%	0.5%	-1.5%	1.6%	1.2%	-0.4%
4	96.3%	98.3%	2.0%	0.2%	0.3%	0.1%	1.1%	0.4%	-0.6%	1.3%	0.3%	-1.0%	1.1%	0.7%	-0.4%
BE-starters															
	STEM			BE			SSH			OP			Drop		
BE-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	0.9%	2.0%	1.1%	91.1%	89.8%	-1.3%	2.4%	1.7%	-0.8%	2.9%	2.4%	-0.5%	2.7%	4.2%	1.5%
2.5	0.7%	1.5%	0.8%	92.6%	92.4%	-0.2%	2.0%	1.2%	-0.8%	2.4%	1.8%	-0.7%	2.3%	3.1%	0.8%
3	0.6%	1.1%	0.5%	93.9%	94.4%	0.5%	1.7%	0.9%	-0.8%	2.0%	1.3%	-0.7%	1.9%	2.3%	0.4%
3.5	0.5%	0.8%	0.3%	94.9%	95.9%	1.0%	1.4%	0.7%	-0.7%	1.7%	1.0%	-0.7%	1.5%	1.7%	0.1%
4	0.4%	0.6%	0.2%	95.8%	97.0%	1.2%	1.1%	0.5%	-0.6%	1.4%	0.7%	-0.7%	1.3%	1.2%	0.0%
SSH-starters															
	STEM			BE			SSH			OP			Drop		
SSH-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	1.9%	4.7%	2.7%	1.3%	4.0%	2.7%	82.7%	74.6%	-8.2%	5.4%	5.7%	0.3%	8.6%	11.0%	2.4%
2.5	1.4%	3.3%	1.9%	1.0%	2.9%	1.9%	87.4%	82.1%	-5.2%	4.0%	4.1%	0.1%	6.3%	7.6%	1.4%
3	1.0%	2.2%	1.2%	0.7%	2.0%	1.3%	90.9%	87.8%	-3.1%	2.9%	2.8%	-0.1%	4.5%	5.2%	0.7%

3.5	0.7%	1.5%	0.8%	0.5%	1.4%	0.9%	93.5%	91.9%	-1.6%	2.1%	1.8%	-0.2%	3.2%	3.4%	0.2%
4	0.5%	1.0%	0.5%	0.4%	0.9%	0.5%	95.4%	94.7%	-0.7%	1.5%	1.2%	-0.3%	2.3%	2.2%	0.0%
OP-starters															
	STEM			BE			SSH			OP			Drop		
OP-GPA	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff	Female	Male	Diff
2	1.3%	2.2%	0.9%	0.9%	2.9%	2.0%	3.7%	3.6%	-0.1%	83.0%	80.9%	-2.1%	11.0%	10.4%	-0.7%
2.5	1.0%	1.6%	0.6%	0.7%	2.1%	1.4%	2.7%	2.6%	-0.1%	87.8%	86.3%	-1.5%	7.9%	7.4%	-0.5%
3	0.7%	1.1%	0.4%	0.5%	1.5%	1.0%	1.9%	1.8%	0.0%	91.4%	90.4%	-1.0%	5.6%	5.2%	-0.4%
3.5	0.5%	0.8%	0.3%	0.3%	1.0%	0.7%	1.3%	1.3%	0.0%	94.0%	93.3%	-0.7%	3.9%	3.6%	-0.3%
4	0.3%	0.5%	0.2%	0.2%	0.7%	0.5%	0.9%	0.9%	0.0%	95.9%	95.4%	-0.4%	2.7%	2.5%	-0.2%

Additionally, female students are not only more likely to persist in SSH than their male counterparts at given grade levels, but also are more likely to migrate to SSH and OP. These results, again, affirm our baseline findings that stronger sensitivity to grades, rather than being a gender-specific phenomenon, is more likely to reflect gender differences in the underlying preferences for academic fields.

3. Proofs of results in Section 6 of the paper

Proof of Lemma.

Consider student optimization problem (5) student of ability level a whose utility function has the weight coefficients α_m for $m = k, j$ and γ, which is formulated in terms of choosing a major and the effort level to exert within it. Let $V_m(a, \alpha_m, \gamma)$ stand for the value function of the problem of maximizing the utility function U by a student of ability level a and weight coefficients α_m, γ within major m, i.e., the highest welfare the student can achieve were he/she to pursue major m. This means that problem (5), where student index *i* is dropped for brevity, for the student can be stated as that of choosing between majors with the higher of the values $V_k(a, \alpha_k, \gamma)$, $V_j(a, \alpha_j, \gamma)$ where

$$V_m(a, \alpha_m, \gamma) = \max_e \; U = \alpha_m u(ae) - v(e) + \gamma s(g_m(ae)) \tag{A.1}$$

Let a student of ability level a' and utility function weight coefficients α_m for $m = k, j$ and γ prefer major k over major j, or be indifferent between the two, i.e.,

$$V_k(a', \alpha_k, \gamma) \geq V_j(a', \alpha_j, \gamma) \tag{A.2}$$

and let $a'' > a'$. We shall prove that students of ability a'' with the same utility weights will strictly prefer major *k* over major *j*.

Using the Envelope Theorem, we can write for major *m=k, j*:

$$\frac{\partial V_m}{\partial a} = \alpha_m u'(ae_m(a))e_m(a) + \gamma s'(g_m(ae_m(a)))g'_m(ae_m(a))e_m(a) \qquad \text{(A.3)}$$

where $e_m(a)$ is the student's optimal level of effort in major *m* as defined by (A.1). Then, according to the first order conditions of optimum in (A.1), we can rewrite expression (A.3) as:

$$\frac{\partial V_m}{\partial a} = \beta v'(e_m(a))\frac{e_m(a)}{a} \qquad \text{(A.4)}$$

This expression increases in the effort argument $e_m(a)$ since function $v(.)$ is convex. It now remains to refer to Assumption 1, which implies that $e_k(a) > e_j(a)$, so according to (A.4), $\frac{\partial V_k}{\partial a} > \frac{\partial V_j}{\partial a}$. Combining this with (A.2), it is straightforward to conclude that $V_k(a'', \alpha_k, \gamma) \geq V_j(a'', \alpha_j, \gamma)$ for any $a'' > a'$, as required.

The proof of the complementing result: if a student of given ability prefers the less demanding major j over major k or is indifferent between the two, then student of a lower ability will have the same preference, is completely analogous to the above. We have thus established that controlling for the utility weight coefficients, the difference between a student's valuation of the two majors,

$$V_k(a, \alpha_k, \gamma) - V_j(a, \alpha_j, \gamma)$$

strictly increases in student's ability. According to Lemma's provision, this difference is positive for ability levels above the threshold, and negative for those below it. This completes the Lemma's proof regarding threshold $a_{k/j}$. The proofs regarding thresholds $a_{k/0}$ and $a_{j/0}$ proceed along the same lines but simplified by the fact that $\frac{\partial V_0}{\partial a} = 0$. ■

Proof of Proposition 1.

Let a student of ability level $a^0 = a^0(k, j)$ and utility function weight coefficients α^0, γ^0 be indifferent between majors *k* and *j*, as per Lemma, i.e.,

$$V_k(a^0, \alpha_k^0, \gamma^0) = V_j(a^0, \alpha_j^0, \gamma^0) \qquad \text{(A.5)}$$

According to the Envelope Theorem applied to problem (7), we can write:

$$\frac{\partial V_m}{\partial \alpha_m} = u(ae_m(a)) \qquad \text{(A.6)}$$

$$\frac{\partial V_m}{\partial \gamma} = s(g_m(ae_m(a))) \qquad \text{(A.7)}$$

Since, according to (A.6), $\frac{\partial V_k}{\partial \alpha_k} > 0$ for any α_k, (A.5) implies that

$V_k(a^0, \alpha_k^1, \gamma^0) - V_j(a^0, \alpha_j^0, \gamma^0) > 0$ for any $\alpha_k^1 > \alpha_k^0$. Applying the reasoning in the proof of Lemma to this inequality implies that the ability threshold $a^1 = a^1(k, j)$ such that $V_k(a^1, \alpha_k^1, \gamma^0) = V_j(a^1, \alpha_j^0, \gamma^0)$ is lower than the threshold $a^0 = a^0(k, j)$ defined by equality (A.5). In other words, the ability threshold at which a student is indifferent between the majors *declines* in the strength α_k of her taste for more demanding major *k*. This proves result (i) of the Proposition.

Following completely analogous logic, $V_k(a^0, \alpha_k^0, \gamma^0) - V_j(a^0, \alpha_j^1, \gamma^0) < 0$ for any $\alpha_j^1 > \alpha_j^0$, and so the reasoning in the proof of Lemma 1 then implies that the ability threshold at which $V_k(a^2, \alpha_k^0, \gamma^0) = V_j(a^2, \alpha_j^1, \gamma^0)$ is higher than $a^0 = a^0(k, j)$, such that the ability threshold at which a student is indifferent between the majors increases in the strength α_j of her taste for less demanding major *j*. This proves result (ii) of the Proposition.

Finally, to prove result (iii), we shall derive inequality

$$\frac{\partial V_k}{\partial \gamma} < \frac{\partial V_j}{\partial \gamma} \qquad \text{(A.8)}$$

for any γ, from additional parametric conditions on coefficients α_m for *m=k,j*.

According to expression (5) for the value functions of student utility maximization problems by major, equality (A.5) can be restated as

$$\gamma\left[s(g_k(ae_k(a))) - s(g_j(ae_j(a)))\right] = -\left[\alpha_k u(ae_k(a)) - \alpha_j u(ae_j(a))\right] + \left[v(e_k(a)) - v(e_j(a))\right] \quad \text{(A.9)}$$

According to expression (A.7), inequality (A.8) is equivalent to the left-hand side of equality (A.9) being negative, i.e.,

$$\alpha_k u(ae_k(a)) - \alpha_j u(ae_j(a)) > v(e_k(a)) - v(e_j(a))$$

whereas we note that $u(ae_k(a)) - u(ae_j(a)) > 0$ and $v(e_k(a)) - v(e_j(a)) > 0$ since $e_k(a) > e_j(a)$ and both functions are increasing. According to (3), we can rewrite the above inequality as

$$\alpha_k u(h_k(g_k)) - \alpha_j u(h_j(g_j)) > v\left(\frac{h_k(g_k)}{a}\right) - v\left(\frac{h_j(g_j)}{a}\right)$$

According to Largrange formula, this will hold if

$$\alpha_{\min} u'(\theta)\left[h_k(g_k) - h_j(g_j)\right] > v'(\chi a^{-1})\left[h_k(g_k) - h_j(g_j)\right] a^{-1},$$

i.e.,

$$\alpha_{\min} > {v'(\chi a^{-1})}\Big/{au'(\theta)} \quad \text{(A.10)}$$

where $\alpha_{\min} = \min\left\{\alpha_k, \alpha_j\right\}$ and $\theta, \chi \in \left(h_j(g_j), h_k(g_k)\right)$.

Since u(.) is concave and v(.) is convex, inequality (A.10) will hold, if as stipulated in the Proposition, the weights α_k and α_j student places on her tastes for human capital associated with respective majors are large relative to the weight on disutility of effort (which as we recal has been normalized to 1) per following parametric condition:

$$\alpha_{\min} > {v'(\underline{a}^{-1} h_k(\overline{g}))}\Big/{\underline{a} u'\left(h_k(\overline{g})\right)}$$

where as defined earlier, $\underline{a}$ is the lower bound on ability while $\overline{g}$ is the highest grade in the grading scale. As argued above, this condition ascertains inequality (A.8), which in turn implies that $V_k(a^0, \alpha^0, \gamma') < V_j(a^0, \alpha^0, \gamma')$ holds for any $\gamma' > \gamma^0$. This completes the proof of result (iii) and Proposition 1 overall. ∎

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